Special Items, Financial Reporting and Equity Valuation

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Special Items, Financial Reporting and Equity Valuation

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ABSTRACT

This thesis examines the information content of earnings components conditional on the existence of misclassification of core earnings as transitory earnings in the income statement (often referred to as classification shifting), and how this misclassification is likely to induce a "hidden" core earnings element in reported transitory earnings. The thesis focuses on a major type of the misclassification of earnings line items, namely the transfer of negative core earnings (operating expenses and losses) to negative special items in order to increase net core earnings, while bottom-line earnings remain unaffected. The thesis comprises three empirical essays.

In the first essay, we develop a vector autoregression (VAR) of a set of accounting information that includes, in addition to other accounting variables, two components of transitory earnings; a shifted core earnings component and a purified transitory earnings component. The model analysis derives two properties of shifted core earnings. First, shifted core earnings forecast future abnormal earnings similar to core earnings. Second, shifted core earnings provide a "bad news" signal of management incompetence. Using special items as an objective measure of transitory earnings, we develop an innovative approach to decompose special items into core and transitory components. Our empirical results support the former property of shifted core earnings, and show little evidence for the latter one. The model demonstrates how the properties of the transitory earnings components map into stock prices. However, we find empirically that stock prices do not fully reflect the heterogeneity between the two components of transitory earnings, but rather overstate the shifters' entire special items, which are mostly income decreasing items, as if they are all shifted core earnings.

In the second essay, we investigate the manager's incentive to misclassify negative core earnings as negative special items, and the change in the composition of negative special items as a result of the misclassification. We find that large negative special items are increasing with the difference between reported core earnings in the prior period and expected core earnings in the current period. Extremely large negative special items are more likely associated with GAAP-violation rather than allowable discretion within GAAP. We distinguish between two types of misclassification signals, an "informative" signal associated with steady improvements in negative special items predictability and a "noisy" signal associated with a pattern in earnings response coefficients (ERC) that is inconsistent with improvements in negative special items

predictability. We propose and find that the measures of negative special items predictability of future earnings go hand-in-hand with the extent of an informative signal based on the difference between reported core earnings in the prior period and expected core earnings in the current period. However, stock prices do not fully impound information in this identified informative signal, and react to a “noisy” reporting signal that is based on the level of earnings before special items in the income statement.

In the third essay, we investigate whether analysts fully understand the nature and quality of negative special items when they adjust actual earnings and whether their future earnings forecast incorporates the actual persistence of negative special items components. We identify an alternative direct approach to measure the core and transitory elements of negative special items. We validate our measures by showing that the identified core component is more persistent and has very low asymmetric timeliness relative to the identified transitory component. We expand our decomposition of negative special items further in order to examine the nature of negative special items included in and excluded from street earnings. We find that the analysts’ inclusion decision reflects analysts’ expertise in processing information in special items. The analysts’ treatment of negative special items does not lead to predictable forecast errors, consistent with analysts fully understanding the persistence of negative special items components. This result is robust to partitioning the sample between different disclosure and information environments and adding analysts forecast efficiency controls.

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To my parents, wife and kids

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Chapter 1: Introduction

Standard textbooks on financial statement analysis suggest the exclusion of special items when forecasting future earnings. This is because special items have significantly lower information content than core earnings. Recent research documents a substantial increase in the magnitude and persistence of negative special items, which is unjustified by corresponding changes in the business environment that could have resulted in recognizing shocks outside core earnings. This line of research proposes that the misclassification of negative core earnings (operating expenses and losses) as negative special items is the main factor behind the change in the special items reporting strategy over time. This implies that pooling economically different earnings components as being "special items", when forecasting earnings, may result in loss of information.

This thesis examines the information content of earnings components conditional on the existence of misclassification of core (recurring) earnings as transitory (nonrecurring) earnings in the income statement, and the extent to which this misclassification induces a "hidden" core earnings element in nonrecurring earnings. The thesis consists of a literature review chapter and three empirical chapters. Each empirical chapter investigates the phenomenon of misclassification of earnings from certain dimensions including forecasting, market valuation, managers' motives, and analysts' perceptions. Nevertheless, all empirical chapters are self-contained, have different sample data, and can be read independently.

Chapter two, *Accounting Earnings Information Content and Market Valuation*, reviews the literature on the information content of accounting earnings and the relation between accounting earnings and security prices. The chapter dedicates specific attention to the concept of transitory earnings and the use of special items as an objective measure of transitory earnings.

Chapter three, *Classification Shifting, Abnormal Earnings Dynamics, and Stock Valuation*, develops a theoretical foundation for classification shifting and provides empirical evidence on the forecast and value relevance of (negative) core earnings that are shifted to negative special items. The study develops a vector autoregression (VAR) of a set of accounting variables that accommodates, besides other variables, two components of transitory earnings; a core component reflecting shifted core earnings and a transitory component reflecting purified transitory earnings. The model analysis derives two properties of shifted core earnings. Shifted core earnings forecast future abnormal earnings similar to reported core earnings, and shifted core earnings provide a “bad news “signal of management incompetence. Using special items as a measure of a transitory line item that is potentially contaminated by shifted earnings, we provide empirical evidence in support of the former. We propose and find empirically that purified special items are transitory. Nevertheless, our evidence suggests that stock prices do not fully reflect the heterogeneity between the core and transitory components of special items, but rather overstate the entire amount of special items when shifting is suspected.

Chapter four, *On Negative Core Earnings Misclassification,* investigates the motive behind the misclassification, the extent to which this misclassification represents a GAAP-violation or allowable management discretion, the structural change in negative special items in correspondence with the misclassification. We propose and find that the misclassification of negative core earnings as negative special items is a primary factor for large special items reporting. Extremely large negative special items are associated with a drop of expected core earnings in the current period in relation to reported core earnings in the prior period, after controlling for economic conditions, which is consistent with the manager striving to enhance core earnings by taking a misclassification decision. Our results reveal that the manager’s misclassification strategy represents GAAP-violation rather than allowable management discretion. Decomposing negative special items into misclassified core earnings and real special items shows that the misclassified component is associated with subsequent financial restatements, and forecasts earnings as reported core earnings, but receives an ERC (earnings response coefficient) that is inconsistent with its forecasting ability. Further results reveal that stock prices react to information in a “noisy” reporting signal of misclassification. An “informative” signal of misclassification that is associated with an increase in the negative special items persistence, a convergence between negative special items persistence and core earnings persistence, and an improvement in the negative special items *Shorrocks-Shapley* value does not impact the ERC of negative special items accordingly.

Chapter five, *Do Analysts Fully Understand the Quality of Negative Special Items When Negative Core Earnings are Misclassified in the Income Statement?*, investigates the analysts’ adjustment of negative special items in arriving at street earnings. Analysts tracking services, such as IBES, report forms of “street earnings” that reflect the majority of analysts’ decision on the inclusions and exclusions of less persistent earnings items. Negative special items pose a complicated identification problem, because some negative special items represent unusual or infrequent events, and others are strategically reported by managers, which might lead to different implications for future earnings or cash flows. Research documents that the analysts' adjustment of negative special items is made on a firm-by-firm basis rather than on an item-by item basis, such that restructuring charges, for example, can be included in one firm and excluded from another firm in a given period, and this adjustment decision might change in the next period for the same firms. While this suggests that the analysts' decision might be based on some fundamental characteristics of the firm's special items that result in their inclusions in or exclusions from street earnings, very little is known about how analysts process information in negative special items. In this study, we identify new measures that capture core and transitory elements of negative special items. The measures pass validation tests. The identified core component is more persistent and has very low asymmetric timeliness, while the identified transitory component is less persistent and is highly asymmetrically timelier. The measures resemble the adjustment process by analysts, because they identify the components at the firm-year level. Extending this to negative special items included in and excluded from street earnings yield further extended decompositions. We document that analysts are aware of the underlying compositions of negative special items and the motivations and circumstances behind negative special items reporting by the firm. Additionally, the analysts' adjusted negative special items components are not associated with future analysts forecast errors. This latter result is robust to partitions of sample between different disclosure and information environments, or adding controls known to be associated with lower analysts forecast efficiency.

Chapter 2: Accounting Earnings Information Content and Market Valuation

1. Introduction

As a prelude to the research main theme, this chapter reviews related literature in market based accounting research (MBAR). It discusses the information content of accounting variables, with a focus on accounting earnings, and the relation between accounting numbers and security prices. The chapter devotes particular attention to the concept of transitory earnings and the use of special items as an objective measure of transitory earnings.

In their seminal papers, Ball and Brown (1968) and Beaver (1968) provide empirical evidence of the information content of accounting earnings numbers. Their research spawned a considerable body of accounting research that examines the relation between accounting numbers and security prices. Ohlson (1979) classifies this line of research into three broad categories: the valuation of equity, the association of unexpected earnings and unexpected returns, and the forecasting of future returns. Although the findings in Ball and Brown and Beaver create a broad area of accounting research that investigates different dimensions of the return-earnings relation, after two decades of research, Lev (1989) notes that the contribution of earnings towards security prices or returns forecast is still limited. This is because the return-earnings relation does not operate in a vacuum, and is being affected by other factors such as noisiness in earnings and market inefficiency.

The informational perspective of accounting numbers implies that accounting earnings are primitives that signal information to the market. In order for accounting numbers to be value relevant variables, they should map explicitly into equilibrium market prices. This valuation perspective views accounting numbers as economic variables, rather than merely signals, which infer the firm's equity value. Determining the extent of information contained in accounting earnings or their different components, and their implications for future earnings forecast, is an integral part of the valuation process. This is because valuation centers on the earnings forecasting process. Therefore, understanding the evolution of different components of earnings assists in understanding how these components are valued by the market.

The remainder of the chapter is organized as follows. Section 2.2 discusses the informational perspective of accounting numbers and the earnings response coefficient. Section 2.3 reviews the main research on the times series of accounting earnings, and section 2.4 reviews abnormal earnings dynamics and valuation models. Section 2.5 presents the concept of transitory earnings. Section 2.6 reviews research on special items. It defines special items, discusses the increasing magnitude of special items reporting, assesses the use of special items to measure transitory earnings, and discusses the manager's misuse of negative special items to hide core recurring losses. Section 2.7 concludes the chapter.

2. Information Content and Value Relevance of Accounting Numbers

2.1 Information Content Defined

Information is generally defined as the portion of available data that is useful for a certain purpose (Taylor 1979), or a change in expectations about possible outcomes of a particular event (Theil 1967). Announcement of accounting data such as the release of an earnings report and dividends declaration are said to have *information content*, should they change expectations about a particular event to a revised probability distribution of possible states (Taylor 1979, Beaver 1968). If the market is efficient, in the sense that it reflects quickly newly arrived information, a change in security prices around the accounting event date suggests that the accounting numbers release conveys information that alters the market prior expectations about future cash flows. Hence, accounting information about a particular firm manifests itself by a change in its security return (Ball and Brown 1968, Foster 1981 and Kothari 2001). This information perspective suggests that accounting numbers (e.g. annual earnings) act as signals and primitives that convey information. The market uses the information contained in the accounting signals to infer the inputs of valuations models (e.g. discounted cash flows) (Watts and Zimmerman 1990, Penman 1983).

Taylor (1979) describes a framework in which the release of an accounting number has information content. Assuming a particular accounting event as the only signal at the current period, the information content of an accounting event is implied from an inequality between the probability distribution of possible states of a particular object of interest (e.g. expected future earnings or cash flows) conditional upon available information prior to an accounting event and the corresponding distribution conditional upon an expanded set of information that includes the accounting event. This can be written as:

$$\Pr\left(A_i \mid \mathrm{O}_t^S, \mathrm{O}_t\right) \neq \Pr\left(A_i \mid \mathrm{O}_t\right), \quad i = 1 \ldots n \tag{1}$$

where A_i is the possible states of the object of the study, O_t^S is the information contained in accounting event, i.e. the accounting signal; and O_t is the information set available prior to the accounting event.

In this setting, the information content of an accounting event O_t^S is :

$$\mathrm{O}_t^S = \sum_{i=1}^{n} \Pr\left(A_i \mid \mathrm{O}_t^S, \mathrm{O}_t\right) \log\left[\frac{\Pr\left(A_i \mid \mathrm{O}_t^S, \mathrm{O}_t\right)}{\Pr\left(A_i \mid \mathrm{O}_t\right)}\right] \tag{2}$$

If the market is efficient in its semi-strong form, where security prices reflect all publicly available information, the inequality in equation (1) can also be expressed in terms of security prices (Fama 1976), as follows:

$$P_t \neq E\left(P_t \mid \mathrm{O}_t\right) \tag{3}$$

where P_t is an efficient price that incorporates all available information $\left(\mathrm{O}_t^S, \mathrm{O}_t\right)$

Equation (1) and equation (3) indicate that an accounting event has information content, if it results in revised expectations of profitability, for example, which is reflected in price change. An operational framework that illustrates how an accounting event contains information and signals that alter expectations and assessments of a particular event is presented in Figure (1).

The informational perspective of accounting events views accounting numbers as signals or primitives that change the market expectations. A step further suggests that accounting numbers are economic variables explicitly relate to value (i.e. value relevant) rather than merely signals of information, if they properly map into a valuation model (Beaver et al. 1980, Ohlson 1995, Ohlson 1999, Feltham and Ohlson 1995). In this sense, one can view the accounting signal as an accounting variable X_t that is value relevant if it satisfies the following valuation function:

$$P_t = \alpha X_t + \upsilon_t \tag{4}$$

where X_t is an accounting variable at time *t*, α is the valuation coefficient of the accounting variable, and υ_t is Other information at time *t*.

Equation (4) implies that, in order for an accounting variable to be value relevant, one needs to specify a function that relates equity value from the concept of the underlying accounting variable.

2.2 The Information Content of Accounting Earnings

Positive economics theory, efficient market hypothesis and Fama et al.'s (1969) event study are the impetus to Ball and Brown (1968) and Beaver (1968) seminal papers that spawned a stream of market based accounting research (MBAR). Doubts on the information content of accounting numbers motivate Ball and Brown and Beaver to empirically investigate whether published accounting numbers convey information to the market (Kothari 2001).

Building on concurrent capital market theory that suggests capital market efficiency and price adjustment to newly arrived information, hence stock price changes infer the flow of information to the market; Ball and Brown (1968) provide empirical evidence of a significantly positive correlation between the sign of abnormal return in the month of an earnings announcement and the sign of income number change from the preceding year. Their evidence reveals the usefulness of information contained in accounting income numbers, because the market reacts in the same direction as unexpected income. To this end, earnings are separated into two components; expected and unexpected earnings using two earnings expectation models: a regression model and a naïve forecasting model (a simple random walk model). Stock returns are also divided into normal and abnormal components. If a negative (positive) earnings forecast error, defined as bad news (good news), results in a firm's stock return being lower (higher) than expected, earnings numbers are alleged to convey information to the market.

Beaver (1968) obviates the need to specify an earnings expectation model via using two information content measures; price and volume test. A price test targets the overall change in the market expectations, while a volume test concerns with the expectations of individual investors. Beaver's (1968) notion is that an earnings announcement period is likely to have greater price volatility (price test) and higher trading volume (volume test) than other periods, because earnings convey information to the market. His empirical findings support the informational contention of accounting earnings numbers.

Though Ball and Brown (1968) evidence suggests that earnings contain much of the firm's information; most of this information is expected by the market before issuing the annual report by other information sources such as interim reports and dividends announcements. Therefore, more information in annual reports is supplied by alternative sources that make annual reports release not a timely source of information. Foster (1981) provides evidence of other competing sources of information, and documents that the release of annual reports of other firms is a part of the information set that affects the stock prices of firms in the same industry.

The evidence that other competing information sources preempt annual earnings release is consistent with the notion that longer reporting lag to the date of earnings release is associated with less stock return variability because investors seek for substitute sources of information perhaps by other firms' earnings releases in the same industry as suggested by Foster (1981). Nevertheless, Chambers and Penman's (1984) empirical evidence on the relation between the reporting lag and stock price reaction doesn't support this prediction. Defining timeliness as the period between the end of the fiscal year and the issuance of report, they provide evidence of insignificant relation between the variability of stock returns associated with interim and annual reports and the timeliness of the report. Their analysis is conducted on interim and annual earnings announcements of 100 firms from New York Stock Exchange and covers the period 1970-76. In this sense, accounting earnings do convey information to the market that is not supplied by other sources, despite the reporting time lag.

Landsman and Maydew (2001) replicate the Beaver's (1968) study to examine the informativeness of quarterly earnings over the period 1972-98. Using a sample of 90,000 firm-quarters, their evidence reveals an increase over time in the information content of quarterly earnings.

2.3 The Return Earnings Relation and the Earnings Response Coefficient

Given that accounting income numbers have information content, Kormendi and Lipe (1987) examine another dimension to this information and its linkage with equity valuation. They focus on whether the magnitude of the relation between unexpected earnings and security returns relates to the time series properties of earnings (persistence), considering its valuation implication. In this context, an earnings response is defined by Collins and Kothari (1989) as the degree of the co-movement between stock returns and shocks to an earnings series without implying that the latter causes the former. It is a statistical measure of the strength of the market reaction to a dollar of unexpected earnings (Feltham and Pae 2000). The earnings response coefficient is therefore expressed mathematically as follows:

$$RET_t = \beta_0 + \beta_1 UE_t + \varepsilon_t \tag{5}$$

where RET_t is risk adjusted return, β_1 is the earnings response coefficient (ERC), and UE_t is unexpected earnings.

Equation (5) indicates that one can infer the information content of earnings based on the significance of the ERC and the explanatory power R^2 of the model. The return earnings model is estimated using cross section and time series analyses in event or association studies.

Kothari (2001) distinguishes between both types of studies. An "event" study examines whether an accounting event, such as earnings announcement, has information content revealed by changes in stock return and trading volume over a short period of time around the accounting event. The focus of this type of studies is on testing whether earnings convey information to the market that revises its expectations of future cash flows and therefore leads to a change in stock returns. Early examples of event studies include Ball and Brown (1968), Ball and Kothari (1991) and Vincent (1999). An "association" study tests for the positive correlation between accounting numbers and stock returns over a long period of time. In essence, it investigates whether accounting earnings measures capture changes in information set reflected in stock prices, without inferring causality between accounting information and stock price change. Ball and Brown (1986) conduct both event and association studies, other examples of association studies include Collins and Kothari (1989), Easton et al. (1992) and Dechow (1994).

Relaxing the assumption that ERC is cross-sectionally and temporally constant, Collins and Kothari (1989) investigate four temporal and cross-sectional effects on estimated ERC, namely; risk free rate of return, earnings persistence, systematic risk and growth opportunities not captured by persistence. Consistent with their modeling, their empirical evidence reveals that ERC varies positively with persistence and growth and inversely with interest rates and systematic risk. This indicates that ERC depends not only on persistence as in Kormendi and Lipe (1987), but also on other information such as risk, return and growth opportunities.

Using a book value model and an earnings model, and assuming clean surplus and Miller and Modigliani (1961) dividends irrelevance proposition, Easton and Harris (1991) show an association between stock returns and both the *level* and *change* of earnings each scaled by lagged price, such that:

$$\left(\Delta P_t + DV_t\right) / P_{t-1} = \kappa\, \rho\left[\Delta E_t / P_{t-1}\right] + \left(1-\kappa\right)\left[E_t / P_{t-1}\right] + \varepsilon_t \qquad (6)$$

where DV_t is dividends, ρ is the earnings valuation coefficient in a simple regression of price on earnings, and κ is the weight coefficient.

Using a sample of firms during the period 1969 to 1986, Easton and Harris (1991) provide empirical evidence that both earnings level and earnings change deflated by lagged price are relevant for explaining returns. Moreover, the two independent variables are *complements* rather than substitutes, because when both variables are considered together, more security return variations are explained.

Ali and Zarowin (1992) support the evidence in Easton and Harris (1991) and argue that the earning level variable enters the return earnings association because of the presence of *transitory* components in annual earnings. In this sense, the earnings level variable is an additional proxy for unexpected earnings when prior period earnings include a *transitory* component. Their empirical evidence reveals that the explanatory power of the return earnings regression increases with the inclusion of earnings level as an explanatory variable and the presence of transitory components in prior period earning.

2.4 The Information Contained in Earnings Components: Does Earnings Decomposition Provide Additional Information?

Kothari (2001) reports that one reason for research on the properties of earnings components is to examine whether earnings components possess additional information than aggregate earnings. Results in Ball and Brown (1968), Beaver and Dukes (1972), Gheyara and Boatsman (1980), Ro (1980), Rayburn (1986), Lipe (1986), Wilson (1986), Clubb (1995) and Cheng and Yang (2003) among others are mixed. The conclusion is that some components of earnings have more information content while others do not.

Lipe (1986) investigates the incremental informativeness of a set of earnings components - gross profit, general and administrative expense, depreciation expense, interest expense, income taxes and other items- beyond aggregate earnings in association with security returns. The analysis in Lipe (1986) extends Kormendi and Lipe (1987) to test for return reaction to the earnings components shocks. In a sample of 81 firms for the period 1947 to 1980, the evidence reveals that the earnings components innovations are positively related to the earnings components persistence, which implies that the market reacts differently to earnings components based on their time series properties.

Wilson (1986) tests for the information content of two components of earnings: accruals and cash from operations and two accrual variables: current accruals and long term accruals. Defining current accruals as cash flow from operations less working capital and long term accruals as working capital from operations less earnings, he finds evidence consistent with total accrual and cash components having additional information content beyond aggregate earnings. In addition, total accruals are more informative than cash, and current accruals possess information while long term accruals do not. Rayburn (1986) tends to support the evidence in Wilson (1986).

Using a UK sample of 48 companies for the period 1955 to 1984, Clubb (1995) investigates the relative information content of cash flow and earnings. The evidence suggests that earnings numbers are superior to cash flow numbers in association with stock returns. In addition, unexpected working capital from operations and unexpected long term accruals have incremental information content beyond operating, investment and financing cash flows. Clubb (1995) ascribes his findings to the behaviour of the UK market that reacts to current and noncurrent accruals as if they provide additional information not obtained by cash flow data.

In contrast, using a sample of 324 firms for the period 1971-81, Bowen et al. (1986) investigate whether accrual earnings *vis-a-vis* a range of cash flow measures have information content with respect to future cash flows. Their evidence reveals that earnings numbers do not outperform cash flow numbers in forecasting future cash flows.

3. The Time Series of Accounting Earnings Numbers

3.1 The Time Series Properties of Annual and Quarterly Earnings

The Ball–Brown analysis (1968) motivates interest in forecasting accounting income numbers. Their rationale to relate unexpected returns to unexpected earnings, in order to test for the information content of earnings, requires expectations of accounting earnings, which can be derived via time series models. Hopwood and Newbold (1980) argue that another concern of accounting research in time series-forecasting models for accounting earnings is assessing the possibility that managers use discretion to smooth earnings. The intuition is that if a change in accounting practice brings reported earnings closer to a target earnings number that was previously determined using a time series-forecasting model, managers are deemed to smooth earnings. Additionally, accounting numbers-forecasts using time series analysis is to some extent problematic in the sense that accounting filters out qualitative or non-accounting events and aggregates economic events to record the "bottom line" earnings (Bao et al. 1983).

Early attempts in applying time series analysis to forecast accounting earnings arbitrarily select a time series model that visualizes the income-generating process of firms. Dopuch and Watts (1972) are the first to employ the Box-Jenkins (1970) technique in accounting research[1]. The Box-Jenkins (1970) approach to modeling ARIMA (autoregressive integrated moving average) tends to select a time-series model that best fits a firm-generating process, in order to improve forecasts. ARIMA models can be used for both quarterly and annual data (Hopwood and Newbold 1980).

Bao et al. (1983) argue that the Box-Jenkins approach using ARIMA models provides a more powerful methodological approach than other models. Other evidence suggests that a fitted Box-Jenkins model performs no better than the best random walk model on the annual earnings series

[1] The Box-Jenkins approach to modeling ARIMA (Autoregressive Integrated Moving Average) processes in order to make forecasts includes identifying an appropriate ARIMA process, estimating parameters and testing the model assumptions. [see Box and Jenkins 1970]

(See Albrecht et al. 1980 and watts and Leftwich 1977). Moreover, a parsimonious Box-Jenkins model for quarterly earnings performs as well as a more-detailed Box-Jenkins model (Foster 1977).

Time series studies in accounting analyze either quarterly earnings (Foster 1977, Giffins 1977, Brown and Rozeff 1979) or annual earnings (Ball and Watts 1972, Beaver 1970, Dopuch and Watts 1972, Watts and Leftwich 1977 and Albrecht et al. 1977). Foster (1977) performs a study that is similar to Ball and Brown (1986), however he uses quarterly earnings and daily returns. He finds that the sign of unexpected quarterly earnings change is significantly associated with the sign of a firm risk adjusted return in the 60 trading days up to the announcement date of each quarter. Kothari (2001) lists four reasons for interest in quarterly earnings forecast. First, the seasonality of quarterly earnings which is due to the seasonal nature of most business activities. Second, quarterly earnings are timelier than annual earnings. Third, quarterly earnings are more powerful in testing market efficiency. Forth, the abundance of quarterly earnings observations compared to annual earnings. Hopwood et al. (1982) compare the additional information contained in quarterly as opposed to annual earnings. Using univariate time-series models and both quarterly and annual earnings streams to predict one year ahead earnings, they provide evidence of information loss in annual earnings which are inferred from the previous annual earnings figure. More specifically, the prediction error variance from annual earnings is 15-21 % higher than that from quarterly earnings. This implies that the ARIMA quarterly earnings time series models can be used to improve the forecasting accuracy of annual earnings.

In a comparison with analysts' forecast, Brown and Rozeff (1978) are the first to find evidence of analysts' forecasts superiority relative to time series models on quarterly earnings figures. Brown et al. (1987) support the evidence in Brown and Rozeff (1978), and relate it to contemporaneous and timing advantages. Conroy and Harris (1987) show that a combination of both time series and analysts' forecasts produces more predictive ability.

3.2 The Joint Time Series of Accounting Variables: Markovian Linear Information Dynamics systems

Ohlson (1979) is an early attempt to construct a linear information dynamics framework for decision variables. Ohlson's (1979) original Markovian dynamics system is a linear autoregressive model that includes all relevant decision variables, including accounting earnings and dividends at time *t*, that affect investors' expectations about future realizations of these variables and stock prices. Though its originality in Ohlson (1979), the dynamics system in Garman and Ohlson (1980) is a more general description of information that maps into stock prices. The information set includes variables that are intuitively fundamental in valuation as accounting earnings and dividends.

The linear information dynamics in Ohlson (1979), Garman and Ohlson (1980) and Ohlson (1989a) generally take the following form

$$z_{t+1} = \Omega\, z_t + \varepsilon_{t+1} \tag{7}$$

The vector z_t contains variables that determine the value of the firm and Ω contains parameters of the linear information dynamics. In this setting, the value of equity can be determined as a function of the information contained in the state variable z_t such that:

$$V_t = V(z_t) \tag{8}$$

Ohlson (1989a) utilizes the Markovian specification analyzed by Garman and Ohlson (1980), however state variables are identified and restrictions are imposed on the evolution of accounting variables in order to yield more parsimonious dynamics. More specifically, the information environment considers three variables: earnings E_t, book value of equity BV_t, and net dividends DV_t, I.e. $z_t \equiv (E_t, BV_t, DV_t)$. Given this definition of z_t, the linear information dynamics system can be written out in full as:

$$E_{t+1} = \theta_{11}E_t + \theta_{12}BV_t + \theta_{13}DV_t + \varepsilon_{t+1} \tag{9}$$

$$BV_{t+1} = \theta_{21}E_t + \theta_{22}BV_t + \theta_{23}DV_t + \varepsilon_{t+1} \tag{10}$$

$$DV_{t+1} = \theta_{31}E_t + \theta_{32}BV_t + \theta_{33}DV_t + \varepsilon_{t+1} \tag{11}$$

The parameters in Ω represent either the degree of persistence of each accounting variable or the contribution of variables towards predicting a specific accounting variable. More specifically, the parameters θ_{11}, θ_{22}, θ_{33} represent the degree of persistence of earnings, book value and dividends, respectively. Other parameters, e.g. θ_{12} represents the effect of current book value on one year-ahead earnings. Ohlson (1989a) demonstrates that z_t can be also extended to include other non-accounting information, υ_t, hence $z_t \equiv \left(E_t, BV_t, DV_t, \upsilon_t\right)$ becomes a four dimensional state. The implication of this extension of the state variable is that a closed form- valuation model that solves for the dynamics system will include other information as one determinant of the market value of equity.

Ohlson (1989a) indicates a powerful property of the dynamics system presented in equations (9) to (11) in deriving an abnormal earnings dynamics equation. He develops the following abnormal earnings dynamic:

$$E_{t+1}^{a} = \left(\omega_1 + R_f\right)BV_t + \omega_2 BV_{t-1} + \omega_3 DV_t + \varepsilon_{t+1} \tag{12}$$

where E_t^a denotes abnormal earnings and is equal to $E_{t+1}^{a} = E_{t+1} - \left(R_f - 1\right)$, $\omega_1 = R_f + \omega_3$, $\omega_2 = -R_f\omega_3$ and $\omega_3 = \theta_{11} + \theta_{13}$. This can also be simplified to an AR(1) process of abnormal earnings:

$$E_{t+1}^{a} = \omega_3 E_t^{a} + \varepsilon_{t+1} \tag{13}$$

The dynamic given by (12) indicates the predictive ability of accounting variables for one period ahead abnormal earnings. Equation (12) is an *autoregressive process* of the first order, AR (1), for abnormal earnings. The analysis in Ohlson (1989a) leads to a more advanced valuation theory in Ohlson (1995) and Feltham and Ohlson (1995).

4. The Abnormal Earnings Dynamics and Closed Form-Valuation Models

4.1 Theoretical Perspective

The use of abnormal earnings dynamics is common in theoretical work that focuses on developing accounting based valuation models and highlighting related accounting attributes (e.g. persistence, conservatism and attributes of earnings components). The assumption of the abnormal earnings evolution feeds through into the derived valuation equation. Parsimonious abnormal earnings dynamics that exclude a structure for book value results in *unbiased* accounting valuation models (Ohlson 1995). This implies that book value of assets is properly measured in the accounting system and has no effect on forecasting future abnormal earnings (Lundholm 1995).

If the abnormal earnings dynamics formula includes a book value structure, this implies that a *conservative* accounting system understates book value and a positive coefficient attached to the book value in the dynamic adjusts for the undervaluation. The positive book value coefficient ensures an upward correction in forecasting future profitability. A resulting valuation model in this sense permits unconditional conservatism to manifest itself by a valuation parameter attached to book value in the valuation function which also articulates with the book value forecasting parameter in the abnormal earnings dynamics (Feltham & Ohlson 1995). More intervention in the linear abnormal earnings dynamic, via including both book value and dividends, is also found to proxy for additional conservatism (Clubb 2013).

The time series behaviour of abnormal earnings in Ohlson (1995) is given via two equations:

$$E_{t+1}^{a} = \omega E_{t}^{a} + \upsilon_{t} + \varepsilon_{1t+1} \tag{14}$$

$$\upsilon_{t+1} = \qquad + \gamma\upsilon_{t} + \varepsilon_{2t+1} \tag{15}$$

where υ_t is current other information that is not captured by accounting, ω is the persistence parameter of abnormal earnings $(0 \le \omega < 1)$, and γ is the persistence parameter of the other information $(0 \le \gamma < 1)$.

The recursive system of abnormal earnings in Ohlson (1995) is an autoregressive process for both abnormal earnings and non-accounting information. The existence of υ_t in the abnormal earnings dynamic implies that other information is an additive shock to next period abnormal earnings. The absence of E_t^a in the dynamic of other information ensures that next period non-accounting information depends on current non-accounting information not abnormal earnings. The process shows that υ_t summarizes events that have not yet affected current book value and accounting earnings (or abnormal earnings), but it must flow through future abnormal earnings.

This captures the lack of timeliness in accounting numbers (Pope 2010). To elaborate on this point, assume a firm signs a contract in the period t (other information, υ_t). The abnormal earnings dynamic in equation (14) implies that this bears upon next period abnormal earnings E^a_{t+1}. This is because relevant non-accounting information turns to earnings in the future (Lundholm 1995).

In order to derive a closed form-valuation model, Ohlson (1995) overlays the assumed abnormal earnings dynamic on an abnormal earnings valuation model that measures the value of equity as the sum of book value and discounted future abnormal earnings.

The Ohlson (1995) model is given by:

$$V_t = BV_t + \alpha_1 E^a_t + \alpha_2 \upsilon_t \tag{16}$$

where $\alpha_1 = \omega / \left(R_f - \omega\right) \geq 0$, and $\alpha_2 = R_f / \left(R_f - \omega\right)\left(R_f - \gamma\right) \geq 0$

The valuation model can be equivalently expressed in terms of normal rather than abnormal earnings such that:

$$V_t = \kappa\left(\varphi E_t - DV_t\right) + \left(1-\kappa\right) BV_t + \alpha_2 \upsilon_t \tag{17}$$

where $\kappa = \left(R_f - 1\right)\omega / \left(R_f - \omega\right)$, and $0 \leq \kappa \leq 1$, $\varphi = R_f / \left(R_f - 1\right)$ is an earnings multiplier

The Ohlson model in equation (17) indicates that the value of the firm is the sum of a weighted average of an earnings model and a book value model plus other information not yet reflected in earnings or book value. κ determines the weight placed on each accounting based model. Therefore the lower bound of κ places all weight on the book value of the firm and the higher bound places all weight on a multiple of current earnings less current dividends.

The assumption that abnormal earnings may converge to zero over time suggests that the dynamic does not accommodate positive net present value (NPV) project opportunities. In other words, the dynamics implicitly imply that firms cannot on average earn in excess of the cost of capital and all expected NPV projects must equal to zero (Lo and Lys 2000). Nevertheless, Ohlson (2003) argues that the Ohlson (1995) model "*allows for positive abnormal earnings, on average, given appropriate parameterization"*. A solution to this drawback, if any, is also obtained by the inclusion of a book value structure in the abnormal earnings dynamic to allow for accounting conservatism, because conservatism results in unrecorded goodwill that may reflect expected future positive NPV projects (Feltham and Ohlson 1995).

4.2 Empirical Evidence

While the autoregressive time series of abnormal earnings is intuitively appealing, there is no economic theory to suggest that the evolution of abnormal earnings over time approximates an AR (1) process for all firms over all time periods. Empirically," *any one-size-fits-all description of the evolution of future cash flows or earnings for a sample of firms is likely to be rejected*" (Kothari 2001). Nonetheless, some empirical results still generally support some aspects in the linear information dynamics system (Dechow et al. 1999 and Barth et al. 1999).

In their direct test of the Ohlson's (1995) linear information dynamics, Dechow et al. (1999) employ a pooled time series and cross sectional regression analysis for a sample of 50,133 annual observations over the period 1976−1999, in order to investigate whether the persistence parameter of abnormal earnings ω differs from its extreme bounds as suggested by Ohlson (1995), the optimal lag length of the autoregressive process, and the constraints placed on the abnormal earnings dynamic. The results reveal that ω = 0.62 with a *t*-statistic of 138.31. The effect of including more abnormal earnings lags in the abnormal earnings dynamic is minor; though a second order term is statistically significant. Therefore a first order autoregressive process is empirically appealing and approximates the abnormal earnings pattern. When book value is added to the abnormal earnings dynamic, the coefficient on abnormal earnings declines, and the coefficient on book value is significantly negative. Though the negative coefficient on book value is suggested as a manifestation of aggressive accounting by Feltham and Ohlson (1995), Dechow et al. (1999) argue the Feltham and Ohlson's (1995) specification is unsatisfactory.

Dechow et al. (1999) examine also the autoregressive process of other information υ_t. Using other information derived from analysts' forecasts as a proxy of υ_t, their evidence shows that the autoregressive coefficient of other information is significantly different from 0 and 1 ($\gamma = 0.32$ with a t-statistic of 57.94). Nevertheless, results show that the information dynamics contribution to valuation is modest and outperformed by utilizing a simple valuation model that capitalizes analysts' earnings forecasts in perpetuity. Further tests attribute this result to an investor behavior effect that overweights (underweights) information in analysts' earnings forecasts (current earnings and book value).

Thought the evidence in Dechow et al. (1999) broadly supports the system of dynamics, the results are relatively disappointing with respect to explaining contemporaneous stock prices (assuming that stock price is a proxy for equity value). Results indicate that the valuation model tends to undervalue equity relative to the market price.

Using UK data, O'Hanlon (1995) provides evidence in support of a zero mean autoregressive process rather than the best fit ARIMA model as an approximation of how the market *weights* earnings variables. One interpretation underlying his results is that*" the market may behave as though residual income is generated by a zero mean autoregressive process even though it is not*". Callen and Morel (2001) extend the one-period lagged-abnormal earnings dynamic in Ohlson (1995) to a two period-autoregressive process[2]. Their intuition is that an AR (2) process is assumed to incorporate more time series paradigms than if it is single lagged. Therefore, an AR (2) closed form-valuation model is expected to yield higher predictions of market prices. Using a sample of 19,789 firm-years from the period 1962 to 1996, Callen and Morel find that both AR (1) and (2) models provide poor estimates of stock prices. In addition, although book values underestimate market values, they approximate market values better than the estimated equity values of the Ohlson model, regardless of the lag structure imposed on the abnormal earnings dynamic. One explanation of their result is that the Ohlson model is mis-specified.

Callen and Segal (2005) argue that the limited empirical validity of the Ohlson (1995) model is probably due to the fact that accounting is biased. Hence, adjusting for biases in accounting is expected to improve the empirical results. Nevertheless, Myers (1999) tests the Feltham and Ohlson (1995) conservative valuation model, and the evidence indicates that the conservatism

[2] Note that the AR (1) abnormal earnings dynamic is theoretically similar to and derived from AR (1) dynamics of accounting variables (See Ohlson 1989a)

parameter in the Feltham and Ohlson's (1995) abnormal earnings dynamic is negative for 60% of firms in the sample, which contrasts with the model assumption. Moreover, Myers (1999) modifies the linear information dynamic system in a manner that allows for conservatism to manifest itself in two parameters; an income parameter and a book value parameter. His intuition is that, while Feltham and Ohlson (1995) suggest that a book value parameter approximates the effect of conservatism on future abnormal earnings (due to understatement of assets), the clean surplus identity ensures that understatement of assets is linked to either overstatement of expenses or understatement of revenues. Therefore, including an additional structure to control for the conservatism income effect is also essential. The evidence shows that neither the Myers' modifications nor the Ohlson's (1995) and Feltham and Ohlson's (1995) dynamics capture aspects of the market valuation process.

Barth et al. (2005) utilize the Feltham and Ohlson framework to test whether earnings disaggregation, dynamics system imposition and by-industry estimation aid in predicting out-of-sample current equity values. They construct three valuation models along with a specific system of linear information dynamics for each model. The first model includes aggregate earnings. The second model decomposes earnings into cash flows and accruals. The third model further decomposes accruals into change in receivables, change in inventory, change in payables and depreciation. Barth et al. (2005) perform prediction error tests across all models, impose the dynamics structure to constraint the valuation parameters, and compare prediction errors from pooled and industry samples for each dynamics system. Using a sample of 14, 128 firm-years over the period 1988 to 2001, their evidence reveals that both earnings disaggregation and prediction of valuation parameters on an industry-basis reduce prediction errors. In addition, imposing the dynamics structure yields significantly smaller prediction errors only in the pooled sample and not across industries.

5. Transitory Earnings

Transitory earnings have been defined as noise or garbling in reported earnings, which is likely to contribute to reducing the value relevance of earnings (See Graham and Dodd 1940, Collin et al. 1997, Easton et al. 2000). This is because reported (observable) earnings are equal to permanent earnings plus transitory earnings, which are both unobservable, and the intrinsic value of the firm is based on its long term permanent earnings. Therefore, a tendency to record more transitory earnings is expected to decrease the value relevance of reported earnings. Evidence in Easton et al. (2000) reveals a reduction in the ERC when reported earnings include one-time earnings items that are generally transitory. Ohlson (1989b) demonstrates that when earnings are permanent, unexpected earnings are captured by earnings change, and when earnings are transitory, unexpected earnings are captured by earnings level. Since earnings contain both permanent and transitory components, unexpected earnings are a weighted average of both earnings change and level. Easton and Harris (1991) use both earnings change and earnings level as explanatory variables of returns, and attribute the loading of earnings level to the existence of transitory earnings in reported earnings. Evidence of presence of transitory earnings is also provided by Brooks and Buckmaster (1976), Ou and penman (1989) and Ali and Zarowin (1992) among others. In contrast to the view that accounting practices garble information about earnings, Ou and Penman (1989) provide evidence that accounting can provide information that filters out transience in earnings. In Ou and Penman (1989), transitory earnings are indeed value relevant aspects of the firm's operations rather than measurement error.

Ohlson (1999) formally defines three attributes of transitory earnings. First, transitory earnings are unpredictable. Second, transitory earnings are irrelevant for forecasting future earnings. Third, transitory earnings are irrelevant for equity valuation. The analysis in Ohlson (1999) extends the Ohlson's (1995) information dynamics, by modeling transitory earnings in order to show the linkage among their three properties. Ohlson's (1999) generalized linear information dynamics system is given by:

$$E_{t+1}^{a} = \theta_{11} E_{t}^{a} + \theta_{12} E_{2t} + \gamma_{1} \upsilon_{t} + \varepsilon_{1t+1} \tag{18}$$

$$E_{2t+1} = \theta_{22} E_{2t} + \gamma_{2} \upsilon_{t} + \varepsilon_{2t+1} \tag{19}$$

$$\upsilon_{t+1} = + \eta \upsilon_{t} + \varepsilon_{3t+1} \tag{20}$$

where E_{2t} is an individual earnings component that is labeled as "transitory earnings" under specific circumstances, θ_{12} is the incremental effect of E_{2t} on forecasting one period ahead abnormal earnings, and θ_{22} is the persistence parameter of E_{2t}.

Using the triangular information structure in equations (18-20), Ohlson (1999) develops the following closed form-valuation model:

$$V_t = BV_t + \alpha_1 E_t^a + \alpha_2 E_{2t} + \lambda \upsilon_t \tag{21}$$

where $\alpha_1 = \theta_{11} / \left(R_f - \theta_{11}\right)$, $\alpha_2 = R_f \theta_{12} / \left(R_f - \theta_{11}\right)\left(R_f - \theta_{22}\right)$, and λ depends on all parameters in the dynamics.

The Ohlson's (1999) valuation model provides significant insights into the link between the two sides of informational relevance: forecasting and valuation relevance for a separate component of earnings. In this setting, Characterizing E_{2t} as "*transitory earnings*" implies three restrictions on the dynamics and the valuation model: Non-predictive ability $\left(\theta_{22} = 0\right)$, forecasting irrelevance $\left(\theta_{11} + \theta_{12} = 0\right)$, and valuation irrelevance $\left(\alpha_1 + \alpha_2 = 0\right)$. Ohlson (1999) further demonstrates that, any two restrictions imply the third, yet one restriction will not imply the other two. However, an earnings component E_{2t} that is unpredictable $\left(\theta_{22} = 0\right)$ can still be forecasting relevant $\left(\theta_{11} + \theta_{12} \neq 0\right)$ under very specific accounting conditions such as hedge accounting.

Barth et al. (1999) utilize the linear information dynamics assumed by Ohlson (1999) to examine some properties of the accrual and cash flow components of earnings. Their evidence reveals that findings are generally consistent with their expectations about different attributes of both components. A favourable interpretation is that the Ohlson's (1999) specification of the time series behaviour of the individual earnings components is empirically descriptive.

Landsman et al. (2011) employ Ohlson (1999) and Barth et al. (1999) to test forecasting and valuation properties of two components of dirty surplus earnings; dirty surplus and really dirty surplus. The former is a component of comprehensive earnings that is excluded from reported earnings, and the latter is a component of earnings that might arise when the firm issues or reacquires its own shares (e.g. conversion of bonds into common stocks). In general, dirty surplus earnings are viewed as transitory earnings with less persistent implications for future earnings. The evidence in Landsman et al. (2011) reveals that the dirty surplus component is forecasting irrelevant and valuation irrelevant; and acts as a transitory earnings component as described by Ohlson (1999). However, really dirty surplus are forecasting irrelevant but valuation relevant. In addition, insignificant (significant) hedge returns are obtained when based on the dirty surplus component (really dirty surplus component). This match between the hedge return results and the Ohlson's (1999) forecasting and valuation link results validates the characterization of transitory earnings in this setting.

In a recent paper, Ohlson (2014) differs from Ohlson (1999) in that transitory noise that is observable can contain some relevant information, but Ohlson (2014) stresses on the idea that the noise is not part of reported earnings. Ohlson (2014) argues that though permanent earnings are never observable regardless how reported earnings are modified, reported earnings can at best approximate permanent earnings. The focus on what accounting information can be used to forecast future earnings and update this forecast leads to whether special items, earnings decompositions, and earnings quality can play a role in equity valuation.

6. Special Items and Transitory Earnings

6.1 Special Items Gains and Losses

Special items are unusual or infrequent earnings that are often reported as a separate component of income from continuing operations in the income statement. Special items are by definition less persistent than other operating income components. The presentation of special items on the income statement allow for managerial discretion in reporting special items as individual line items on the income statement with possibly discussions in the footnotes, or as an aggregate amount on the income statement with only discussions in the footnotes (Riedl and Srinivasan 2010).

Though special items contain positive and negative components of earnings, negative special items are much more common than positive special items (Johnson et al. 2011). The preponderance of negative special items is attributed to the conservative nature of accounting that requires timely recognition of negative shocks to value (bad news). Therefore negative special items act as an account through which accounting conservatism is facilitated, which in turn contributes to the transience of negative special items (Callen et al. 2010). In contrast, positive special items are less common, more difficult to interpret, and often part of broad restructuring transactions that have average negative effects (Elliot and Hanna 1996).

Accounting for special items has been significantly changed over years. These changes affect the timing, measurement, and disclosure requirements for special items (Elliott and Hanna 1996 and Johnson et al. 2011). Alciatore et al. (1998) provide a review of the standards that affect accounting for write downs, which are a major component of special items. As a brief summary, SFAS.5 requires an immediate write down of asset when it is probable that the asset is impaired and the impairment loss can be reasonably estimated. However, SFAS.5 does not provide specific guidelines and results in a wide range of practices employed by firms in accounting for write downs (Elliott and Hanna 1996). SFAS.121, SFAS.144 and SFAS.146 deal more specifically with special items, in order to minimize the inconsistency in practice, which resulted from previous standards. Afterwards, the change in regulations in the 2000s due to the Sarbanes Oxley Act of 2002 and Regulation G of 2003 appear to have some influence on the reporting of special items (Kolev et al. 2008 and Chen 2010).

Literature documents a significant increase in the frequency of special items reporting. Johnson et al. (2011) report that the frequency of special items reporting increases from 22 percent of all firms in year 1980 to 59 percent of all firms in year 2009. The significant increase in special items reporting is due to negative rather than positive special items. While the frequency of negative special items increases from 8 percent of all firms in year 1980 to 44 percent in year 2009, positive special items reporting is 13 percent of all firms in year 1980 and increases only to 15 percent in year 2009. Riedl and Srinivasan (2010) show consistent results to Johnson et al. (2011) using a sample over the period 1978 to 2003.

Frankel (2009) raises concerns in the substantial increase in negative special items reporting by firms. His perspective is that since there are no substantial changes to the business environment that justify the increasing magnitude and reporting frequency of negative special items over years, this casts doubts on the possibility of using negative special items as a tool to hide real recurring expenses that are part of the core operations of the firms.

6.2 Are Compustat Special Items a Reasonable Place to Identify Transitory Earnings?

Compustat codes unusual or nonrecurring items as special items. The Compustat special items variable (annual data item SPI and quarterly data item SPIQ) includes a range of earnings items that result from one-time gains and losses, write offs, restructuring charges, among other earnings with less persistent nature. The Appendix includes the standard format of income statement in Compustat that shows the location of special items within other earnings line items.

According to Compustat, the following are examples of special items:

1. Adjustments applicable to prior years (except recurring prior year income tax adjustments)
2. After-tax adjustments to net income for the purchase portion of net income of partly pooled companies (when the adjustment is carried over to retained earnings)
3. Any significant nonrecurring items
4. Bad debt expense/Provisions for doubtful accounts/Allowance for losses if non-recurring
5. Current year's results of discontinued operations and operations to be discontinued
6. Flood, fire, and other natural disaster losses
7. Gain/loss on extinguishment of debt
8. Impairment of goodwill/unamortized intangibles
9. Interest on tax settlements (when reported separately from other interest expense)
10. Items specifically called "Restructuring/Reorganization", "Special," "Nonrecurring" or Core Earnings Specials regardless of the number of years they are reported
11. Inventory write downs when separate line item or called non-recurring
12. Nonrecurring profit or loss on the sale of assets, investments and securities, if the company has not adopted SFAS #115
13. Profit or loss on the repurchase of debentures
14. Purchased research and development
15. Recovery of allowances for losses if original allowance was a special item
16. Relocation and moving expense
17. Reserve for litigation
18. SFAS 133 related adjustments that the company calls 'one-time' or 'non-recurring
19. Severance pay when a separate line item
20. Special allowance for facilities under construction
21. Transfers from reserves provided for in prior years
22. Write-downs or write-offs of receivables and intangibles
23. Year 2000 expenses regardless of the number of years they are reported

Using a sample from Compustat between 2001–2009, Johnson et al. (2011) report that 39 percent of negative special items are restructuring charges and write-offs, 25 percent are Goodwill impairments, and any other sub-type of negative special items does not represent more than 20% in their sample. With respect to positive special items, gains on disposal of assets are approximately 42 percent and litigation gains are 29 percent of all positive special items.

Though the Compustat's special items variable contains different subtypes of special items, they all have a common feature of being unusual items with less persistent implications for future earnings. The definition of special items in Compustat has been widely accepted as an objective measure of transitory earnings for the following reasons. First, Compustat's definition of special items is a reasonable definition of items with transitory implications for future earnings (Frankel 2009). Second, Compustat seems to filter earnings components searching for items that are on the income statement and its accompanying notes to identify properly the nonrecurring items (Burgstahler et al. 2002). Third, Compustat has no incentive to intentionally bias the measure of special items (Christensen et al. 2011). Fourth, Compustat identification of special items is consistent with that of other market participants (e.g. exclusions from street earnings are highly correlated with Compustat special items) (Bradshaw and Sloan 2002).

Nevertheless, a drawback in the Compustat' identification approach of special items (or even in assuming that special items on the income statement are an appropriate measure of transitory earnings) is that Compustat appears to depend partially on the information provided by management in the annual report. If the earnings item is labeled as nonrecurring in the annual report, Compustat will directly include it in special items (Frankel 2009).

6.3 Are Special Items a "Perfect" Measure of Transitory Earnings?

Misuse of special items aside, the association of special items reporting with complex and unusual economic events such as restructuring charges and write down of assets is alleged to affect adversely the information contained in reported earnings and make the measurement of the recurring component of earnings more complicated. Special items are by definition "unusual" or "infrequent", induce uncertainty for example in the case of success or failure of restructuring, and involve complicated measurement issues which in turn obscure information in operating income (Elliott and Hanna 1996, Riedl and Srinivasan 2010).

In this sense, the effect of special items on reported earnings is similar to that of transitory earnings. One can think of special items as noise or garbling in reported earnings. Indeed, evidence reveals that earnings before special items are more value relevant than operating earnings and that the relevance of earnings before special items decreases when the financial statements contain more special items (Elliott and Hanna 1996). Taken at face value, this is what one would expect from a transitory earnings component.

Notwithstanding this evidence of special items transience, special items are far from a perfect measure of transitory earnings. Some results show that negative special items can still play a role, though being limited and less than that of recurring earnings, in forecasting future profit margin (Fairfield et al. 2009, Hsu and Kross 2011). In addition, the prior reporting of negative special items is related to subsequent reporting (Johnson et al. 2010).

With regard to the market pricing of special items; there are some mixed results. Special items appear to explain future returns in Dechow and Ge (2006), overpriced by the market when only included in rather than excluded from street earnings in Hsu and Kross (2011); and though being viewed as finite horizon events rather than recurring, they induce noise in the information environment in Elliott and Hanna (1996). Burgstahler et al. (2002) also show that the market appears not to fully understand the implications of special items for future earnings.

Ohlson (2006) reports that special items are one of the flaws inherent in GAAP reliance on a balance sheet approach; a write down of assets in the balance sheet will lead to a negative special item charge in the income statement that is viewed as a transitory earnings item, however in *some* cases the realization of this item may influence subsequent recurring earnings.

6.4 Misclassification of Recurring-Nonrecurring Earnings Inducing a Core Composition in Transitory Special Items

Adding to the complications and economic uncertainty surrounding negative special items reporting that contribute to their permanence/transience nature, the literature documents a tendency to misuse negative special items to accommodate shifted recurring expenses. McVay (2006) provides evidence of firms moving recurring expenses into negative special items in order to boost their core earnings. Evidence in McVay (2006) reveals a positive contemporaneous association between unexpected core earnings and negative special items, consistent with the classification shifting of core expenses. Moreover, the improvement in core earnings reverses in the subsequent period when the firm does not repeatedly reports special items.

Classification shifting or misclassification of expenses is an earnings management tool that intentionally misclassifies categories of recurring and nonrecurring expenses in the income statement. By moving recurring expenses into negative special items, core profitability temporarily increases and those moved expenses are more likely to be excluded from pro forma earnings measures. Since investors are influenced by the placement of gains and losses in income statement (Bartov and Mohanram 2014), and the market is increasingly focusing on pro forma earnings (Bradshaw and Sloan 2002, Gu and Chen 2004), management is seeking to temporarily maximize stock price via this misclassification strategy (McVay 2006).

Since its introduction by McVay (2006), the concept of classification shifting has provided some insights into research on earnings management and special items. Fan et al. (2010) replicate the analysis in McVay (2006) using quarterly rather than annual data as in McVay (2006) and a revised core earnings expectation model. Their evidence supports the classification shifting evidence in McVay (2006). Athanasakou et al. (2009) provide consistent evidence of misclassification of expenses in the UK, and that this appears to be more attractive to UK firms than accrual management in order to avoid negative earnings surprises. Interestingly, Kolev et al. (2007) show that managers become recently more engaged in classification shifting after the SEC intervention into non-GAAP reporting (between years 2001 to 2004). Fairfield et al. (2009) find that special items are more permanent (more transitory) for high (low) profitability firms consistent with high profitability firms moving more recurring expenses to special items to maintain higher profitability. More recently, Abernathy et al. (2014) provide evidence of classification shifting being a substitute for both accrual earnings management and real earnings management under certain circumstances.

Evidence also reveals that the misuse of negative special items to conceal recurring expenses is not limited to “within-the-period” shifting, but can be also exercised over periods (inter-period shifting) to improve future performance (Burgstahler et al. 2002 and Cready et al. 2010). Additionally, Kinney and Trezevant (1997) show that managers have also discretion in the timing and magnitude of negative special items reporting. Thereby, negative special items are reported when the firm expects higher than average income in order to smooth earnings, or lower than average income in order to take a big bath.

Frankel and Roychowdhury (2008) demonstrate that both conditional conservatism inherent in GAAP and strategic reporting of negative special items affect the fundamental composition of negative special items. This is because conservatism induces transience in negative special items, and strategic reporting enhances the permanence of negative special items. Callen et al. (2010) show empirically that conditional conservatism is facilitated via negative special items reporting. Heflin et al. (2014) provide evidence of special items capturing conditional conservatism, and that analysts' exclusion of special items from street earnings results in street earnings being less conditionally conservative than GAAP earnings.

The uncertainty and different circumstances associated with negative special items reporting impact the predicted persistence of negative special items and pose a complicated identification problem for analysts when adjusting street earnings. This is because analysts seek to include only earnings items that have high implications for future earnings. While recent evidence by Christensen et al. (2011) documents that the analysts' adjustment process is influenced by management earnings guidance, it does not rule out the possibility that managers are the followers rather than the initiators, and that managers merely respond to the analysts' demands of exclusions and inclusions of earnings items.

7. Conclusion

The present chapter discusses and reviews research on the informational contention of accounting earnings numbers. It focuses on the relation between accounting earnings and stock returns, and the role of transitory earnings.

Evidence is consistent with an information role of unexpected earnings in explaining stock returns (or unexpected returns). Moreover, different earnings components have different value relevant information corresponding to the time series properties of the earnings components. Neoclassical valuation theory assumes a system of accounting information dynamics, which characterizes the stochastic evolution of accounting data, and conjectures a unique valuation solution that maps accounting information into an equilibrium equity value.

Transitory earnings are alleged to obscure information in reported earnings and reduce the value relevance of earnings. Since transitory earnings are unobservable, special items have been used as a measure of transitory earnings. This is justified because special items are less persistent earnings components, and special items reporting is associated with unusual or infrequent economic events that are expected to have less implications for future earnings. Nevertheless, research documents a considerable increase in negative special items reporting that is inconsistent with changes in the business environment which could have led to recognizing shocks outside of the core operations of firms. Evidence documents an improper use of negative special items as a device to conceal core operating expenses. Special items pose a challenge for analysts when adjusting street earnings, because analysts need to assess the recurrability of special items which might be affected by whether special items are economically driven or strategically reported.

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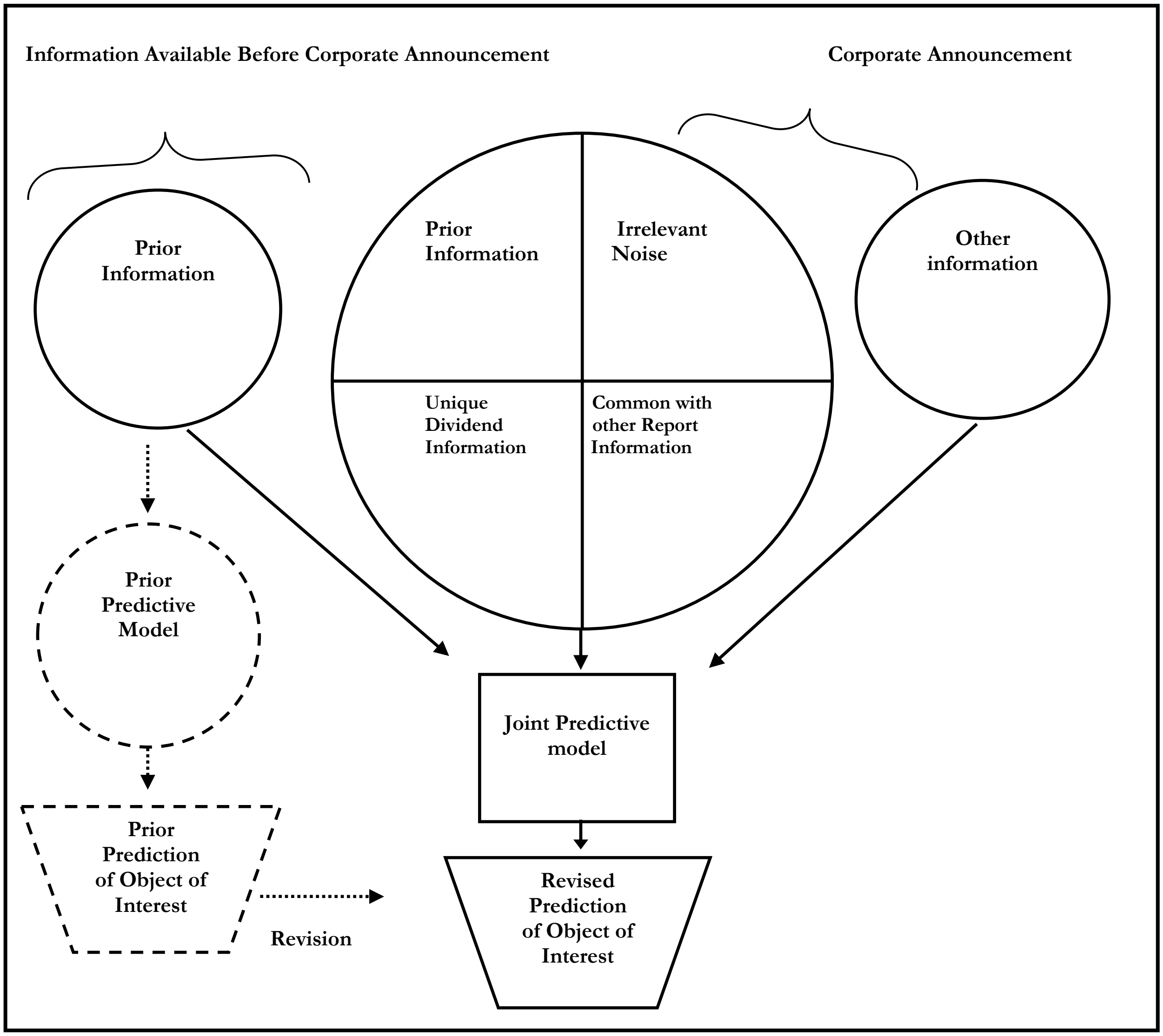
Figures

Figure 1

A Framework for Information Content-Testing (Taylor, 1979)



Appendix

Basic Income Statement in Compustat with Special Items Highlighted

	Annual Data Item	Data Item #
+	Sales (Net)	12
–	Cost of Goods Sold	41
–	Selling, General, and Administrative Expense	189
	Operating Income Before Depreciation	13
–	Depreciation and Amortization	14
	Amortization of Intangibles	65
	Depreciation Expense (Schedule VI)	103
	Depletion Expense (Schedule VI)	174
	Operating Income After Depreciation	178
–	Interest Expense	15
+	Nonoperating Income (Expense)	61
+	*Nonoperating Income (Expense) – Excluding Interest Income*	190
+	*Interest Income*	62
+	Special Items	17
	Pretax Income	170
+	*Pretax Income – Domestic*	272
+	*Pretax Income – Foreign*	273
–	Income Taxes – Total	16
+	*Deferred Taxes (Income Account)*	50
+	Deferred Taxes – Federal	269
+	Deferred Taxes – Foreign	270
+	Deferred Taxes – State	271
+	*Income Taxes – Federal*	63
+	*Income Taxes – Foreign*	64
+	*Income Taxes – State*	173
+	*Income Taxes – Other*	211
–	Minority Interest	49
	Income Before Extraordinary Items	18
–	Dividends – Preferred	19
	Income Before Extraordinary Items – Available for Common	237
+	Common Stock Equivalents – Dollar Savings	191
	Income Before Extraordinary Items – Adjusted for Common Stock Equivalents	20
+	Extraordinary Items and Discontinued Operations	48
+	*Extraordinary Items*	192
+	*Discontinued Operations*	66
	Net Income Adjusted for Common Stock Equivalents	258

Chapter 3: Classification Shifting, Abnormal Earnings Dynamics, and Stock Valuation

1. Introduction

One major type of the misclassification of earnings line items in the income statement is the opportunistic transfer of operating expenses to negative special items in order to increase core profitability, while bottom-line earnings remain unaffected. The Securities and Exchange Commission (SEC) has been actively issuing a number of Accounting and Auditing Enforcement Releases (AAERs) in connection with this classification shifting practice[3].Empirical evidence presented by McVay (2006), Fan et al. (2010) and Alfonso et al. (2015) support the existence of classification shifting in the form of a positive relation between unexpected core earnings and negative special items. A recent study by Abernathy et al. (2014) find evidence of the use of classification shifting as a substitute tool for both accrual earnings management and real earnings management under certain conditions.

In standard accounting-based valuation, market models map accounting variables, which follow a certain time series pattern, into equity values. This pattern is usually characterized by a vector autoregression framework of accounting information (often referred to as "accounting information dynamics") that specifies the evolution of an information set of variables that are fundamental in valuation (Ohlson 1995). Nevertheless, an extensive body of literature shows that stock prices fail to fully reflect information contained in earnings components (Bernard and Thomas 1990, Sloan 1996, Elliot and Hanna 1996, Burgstahler et al. 2002). If stock prices act as if investors fixate on core earnings and are not able to adjust for the misclassification of earnings, classification shifting may result in temporarily higher stock prices.

Research in the area of classification shifting is relatively new and has focused on whether the documented positive relation between unexpected core earnings and negative special items is evidence of classification shifting or is potentially attributable to a statistical fluke. The general belief is that firms move some core expenses and losses into special items to increase earnings before special items and thereby affect stock prices. For this to occur, one has to hypothesize that misclassification obscures the information contained in earnings components, and thus stock prices do not fully impound the true historical forecasting relevance of accounting variables with respect to future earnings. This possibility arises because stock prices reflect investors'

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[3] McVay (2006) and Alfonso et al. (2015) provide some examples of real cases of classification shifting and the firms' AAERs numbers. For more examples; look at the SEC website (www.sec.gov)

expectations of future earnings rather than the true implications of earnings components for future earnings.

In this study, we develop a vector autoregression (VAR) of a set of accounting variables that accommodates, besides other variables, two components of transitory earnings, namely a core component, reflecting shifted core earnings, and a transitory component reflecting purified transitory earnings. The VAR implies an abnormal earnings dynamic and its solution yields closed-form valuation models. One important feature of this framework is that it allows us to theoretically link the VAR transition matrix with coefficients in the abnormal earnings dynamic and valuation models. Hence, each variable's forecasting and valuation coefficient is a function of its persistence and feedback among variables in the VAR. This enables us to calculate the implied theoretical values of coefficients in the abnormal earnings dynamic and valuation models, and then compare these to the coefficients we observe from our estimations for the models using unrestricted regressions.

Using "special items" as a measure of a transitory earnings line item that is potentially contaminated by shifted core earnings, we provide evidence of special items having limited forecasting ability in relation to future abnormal earnings, but the core component of special items that we suspect to be made up by classification shifting forecasts one year ahead abnormal earnings similar to reported core earnings. Our results show that all forecasting coefficients in the abnormal earnings dynamic are consistent with their implied theoretical counterparts derived from the VAR. This suggests that failure to adjust the dynamic (the forecasting model) to reflect explicitly the core component of special items may lead to loss of forecasting-relevant information.

We draw relatively similar conclusions in market valuation with respect to the match between the valuation coefficients and their theoretical values, except for the two components of special items. The results show that the market appears not to be able to correctly price the special items components. Further results reveal that the market can only detect the incidence of shifting but rather applies a higher coefficient on the entire amount of reported special items. Taken together, the evidence in this study, suggests that the market is not able to fully process special items information and value the core and transitory components of special items according to their implications for future profitability. However, the market appears to be able to identify when shifting takes place and applies an incremental valuation coefficient on the shifters' entire amount of special items rather than only the respective shifted component.

In order to execute our tests, we construct an innovative measure of shifted negative core earnings at the firm-year-level that builds on McVay (2006)[4]. We develop an empirical extraction approach that disentangles the core portion of negative special items, which is attributable to classification shifting, from negative special items. Our measure of shifting differs from a recent attempt in Cain et al. (2014) to identify high and low quality special items. Cain et al. (2015) identify low quality special items as comprising past, current, and future operating expenses. However, their identification approach implicitly assumes that all firms reporting negative special items must have been shifting some expenses over periods, and does not account for the possibility that negative special items are entirely reported as a result of poor performance. We focus on current year misclassification and use a different approach that is more specific to small industry groups of firms shifting operating expenses each year. Moreover, our approach requires only one expectation model, while their approach is based on four expectation models which might induce more measurement error.

Our objective is also different from Alfonso et al. (2015) who assign firms as shifters and non-shifters and show evidence of mispricing of shifters' reported core earnings. They label all firms that have positive unexpected core earnings and negative special item or negative discontinued operations as shifters, and argue that their proxy is based on McVay (2006). A limitation of their assignment methodology is that it ignores firms shifting expenses and having less negative unexpected core earnings, which is inconsistent with the intuition in McVay (2006). In this paper, we develop a measure of the core component of negative special items rather than merely identifying shifters. We argue that our measure captures all dimensions of the McVay (2006) analysis for firms that shift expenses and have either positive unexpected core earnings or less negative unexpected core earnings. We also account for firms reporting negative special items as a consequence of deteriorating performance and are less likely to be misusing negative special items to hide their operating expenses.

[4] The terms "operating expenses", "core expenses", and "negative core earnings" are used interchangeably.

The remainder of the paper is organized as follows. Section 2 presents the VAR framework and the forecasting-valuation setup. Section 3 presents the approach used to measure shifted negative core earnings. A description of data and sample used in the study is provided in section 4, and all empirical results are presented in section 5. Section 6 concludes the paper.

2. Vector Autoregression (VAR), Abnormal Earnings Dynamic and Market Valuation

The VAR model is an extension of the information dynamics in Clubb (2013) which builds on previous research by Ohlson (1995), Feltham and Ohlson (1995) and Ohlson (1999). Our analytical models are designed to be as simple as possible and yet provide sufficient scope to represent the key aspects of the phenomenon of interest.

Consider an accounting variables data generating process that follows a first-order VAR system where, as in Clubb (2013), the state vector z_t includes total abnormal earnings ae_t, book value bv_t, and dividends, dv_t :

$$z_{t+1} = \kappa z_t + u_{t+1} \tag{1}$$

The VAR coefficient matrix κ is assumed to be constant over firms and over time. u_{t+1} is a vector of "surprise" movements in the variables after considering current values and feedback among variables. The VAR model can be modified to handle different specifications, while preserving the informational content of the state variable. Consider now the definition of abnormal earnings $ae_t = e_t - (R-1)bv_{t-1}$, where e_t is aggregate earnings and R is one plus risk free interest rate. Since aggregate earnings, e_t, is not a sufficient earnings construct for forecasting and valuation, because earnings components have different information content (Lipe 1986); and classification shifting is assumed to occur within earnings components, we first decompose abnormal earnings into three components: core abnormal earnings, cae_t, "purified" transitory earnings, $pute_t$, and shifted core earnings, sce_t. The earnings variable sce_t is a hypothesized and unobservable earnings component that the manager opportunistically uses to inflate core earnings. Hence, sce_t is, by construction, an earnings component shifted from core to transitory earnings and $pute_t$ is transitory earnings absent classificatory shifting[5]. Our decomposition of the abnormal earnings variable increases the dimensionality of the VAR framework and suggests some parametric restrictions on the κ matrix.

We assume the following modified system in the paper:

$$z_{t+1}\begin{bmatrix} cae_{t+1} \\ pute_{t+1} \\ sce_{t+1} \\ bv_{t+1} \\ dv_{t+1} \end{bmatrix} = \kappa \begin{bmatrix} \kappa_{11} & 0 & \kappa_{13} & \kappa_{14} & \kappa_{15} \\ 0 & \kappa_{22} & 0 & 0 & 0 \\ 0 & 0 & \kappa_{33} & 0 & 0 \\ \kappa_{41} & \kappa_{42} & \kappa_{43} & \kappa_{44} & \kappa_{45} \\ \kappa_{51} & \kappa_{52} & \kappa_{53} & \kappa_{54} & \kappa_{55} \end{bmatrix} \times z_t \begin{bmatrix} cae_t \\ pute_t \\ sce_t \\ bv_t \\ dv_t \end{bmatrix} + u_{t+1} \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \\ \varepsilon_{3t+1} \\ \varepsilon_{4t+1} \\ \varepsilon_{5t+1} \end{bmatrix} \tag{2}$$

where $cae_t = ce_t - (R-1)bv_{t-1}$, and ce_t is reported core earnings. This characterization implies that purified transitory earnings and shifted core earnings sum to reported transitory earnings in the income statement, I.e. $pute_t + sce_t = te_t$, and abnormal earnings can be equally defined as $ae_t = e_t - (R-1)bv_{t-1} = cae_t + pute_t + sce_t$. Restricted zero coefficients on the κ matrix are added for mathematical tractability and have appealing economic intuition. We set $\kappa_{21} = \kappa_{31} = 0$ and $\kappa_{12} = \kappa_{32} = 0$ to allow the current realization of core abnormal earnings and purified transitory earnings to affect future *total* abnormal earnings that include future realizations of these variables via their persistence coefficients κ_{11} and κ_{22}, respectively[6]. However, the differential persistence of these variables suggests that $\kappa_{11} > \kappa_{22}$. Since sce_t is independent of future purified transitory earnings, we set $\kappa_{23} = 0$. We do not restrict κ_{13} to be zero, because sce_t is in essence a core earnings variable that is misclassified in the income statement and is expected to have predictive ability for future core abnormal earnings. This allows sce_t to forecast total abnormal earnings similar to cae_t when $\kappa_{13} + \kappa_{33} = \kappa_{11}$, or results in an *additional signaling* role for sce_t when $\kappa_{13} + \kappa_{33} > \kappa_{11}$. In the empirical analysis, we focus on shifting core expenses to negative special items. Therefore, given that sce_t is a negative earnings variable and $\kappa_{13} + \kappa_{33} > \kappa_{11}$, this implies that sce_t *negatively* predicts future total abnormal earnings similar to

[5] The terms "classification shifting" and "misclassification" are used interchangeably.
[6] Note that total abnormal earnings values are determined by adding the first three rows in the VAR.

core abnormal earnings and acts also as a *bad* news information variable for firms engaging in classification shifting. In other words, if $\kappa_{13} + \kappa_{33} > \kappa_{11}$, sce_t provides relevant information because it is both an earnings variable and an "other information" variable similar to other non-accounting information in Feltham and Ohlson (1995) but in our context of classification shifting.

The clean surplus identity implies that $bv_{t+1} = cae_{t+1} + pute_{t+1} + sce_{t+1} + Rbv_t - dv_{t+1}$, which in turn implies the following coefficients constraints:

$$\begin{aligned}
\kappa_{41} &= \kappa_{11} - \kappa_{51} \\
\kappa_{42} &= \kappa_{22} - \kappa_{52} \\
\kappa_{43} &= \kappa_{13} + \kappa_{33} - \kappa_{53} \\
\kappa_{44} &= \kappa_{14} - \kappa_{54} + R \\
\kappa_{45} &= \kappa_{15} - \kappa_{55}
\end{aligned} \tag{3}$$

Adding the first three rows of the VAR and applying clean surplus yield the total abnormal earnings dynamic expressed in earnings components:

$$ae_{t+1} = \delta_1 ce_t + \delta_2 pute_t + \delta_3 sce_t + \delta_4 bv_t + \delta_5 dv_t + \zeta_{t+1} \tag{4}$$

where the implied forecasting parameters are;

$$\begin{aligned}
\delta_1 &= \kappa_{11} R \\
\delta_2 &= \kappa_{22} - \kappa_{11} + \kappa_{11} R \\
\delta_3 &= \kappa_{13} + \kappa_{33} - \kappa_{11} + \kappa_{11} R \\
\delta_4 &= \kappa_{14} + \kappa_{11} - \kappa_{11} R \\
\delta_5 &= \kappa_{15} + \kappa_{11} - \kappa_{11} R \\
\zeta_{t+1} &= \varepsilon_{1t+1} + \varepsilon_{2t+1} + \varepsilon_{3t+1}
\end{aligned}$$

We call the forecasting model in equation (4); the total abnormal earnings dynamic $(AE - DYNAMIC)$.

When setting stock prices; if investors' expectations of future abnormal earnings reflect the forecasting relevance properties of accounting variables consistent with the VAR estimation and $AE - DYNAMIC$, one can derive an accounting based valuation model by assuming a dividends discount model and applying the valuation procedure in Clubb (2013) whereby the clean surplus coefficient constraints in equation (3) are applied to the valuation function:

$$E[MV_t | z_t] = e_5 \kappa [RI - \kappa]^{-1} z_t \tag{5}$$

where $e_5 = [0,0,0,0,1]$ picks out the valuation coefficients for the z_t variables from the dividends forecast equation, and I is the unit matrix. The solution of equation (5) given the constraints in equation (3) yields the following core abnormal earnings valuation model:

$$MV_t = \beta_1 cae_t + \beta_2 trte_t + \beta_3 sce_t + \beta_4 bv_t + \beta_5 dv_t \tag{6}$$

where the implied valuation multiples are:

$$\beta_1 = \frac{\kappa_{11}(R-\kappa_{44}) + \kappa_{14}\kappa_{41}}{\vartheta}$$

$$\beta_2 = \frac{\kappa_{22}(R-\kappa_{11})(R-\kappa_{44}) + \kappa_{14}(R\kappa_{42} - \kappa_{22}\kappa_{41})}{\vartheta(R-\kappa_{22})}$$

$$\beta_3 = \frac{\left[\kappa_{33}(R-\kappa_{11}) + R\kappa_{13}\right](R-\kappa_{44}) + \kappa_{14}(R\kappa_{43} - \kappa_{33}\kappa_{41})}{\vartheta(R-\kappa_{33})}$$

$$\beta_4 = \frac{(R-\kappa_{11})(R-\kappa_{44}) + \kappa_{14}(R-\kappa_{41)}}{\vartheta}$$

$$\beta_5 = \frac{\kappa_{15}(R-\kappa_{44}) + \kappa_{14}\kappa_{45}}{\vartheta}$$

and; $\vartheta = (R-\kappa_{11}-\kappa_{15})(R-\kappa_{44}) - \kappa_{14}(\kappa_{41}+\kappa_{45})$

The valuation model in equation (6) ensures that if earnings components do not forecast growth in book value (I.e. $\kappa_{41} = \kappa_{42} = \kappa_{43} = 0$) or future core abnormal earnings are not affected by current book value such that $\kappa_{14} = 0$, earnings valuation multiples β_1 and β_2 unambiguously increase by their own persistence coefficients κ_{11} and κ_{22}, respectively, to the extent that $\beta_1 = 0$ when $\kappa_{11} = 0$ and $\beta_2 = 0$ when $\kappa_{22} = 0$. Under the same conditions, β_3, however, is affected not only by its persistence parameter κ_{33} but more importantly by the impact of shifted core earnings on one period ahead core abnormal earnings via κ_{13}. This result is interesting, because it shows that sce_t is expected to contain current value relevant information even if one period shifting is weakly associated with shifting in the next period. In other words, even if shifting core earnings is done temporarily in certain periods to beat analyst forecasts, for example, as found in empirical research and is not a repetitive act by the manager, the valuation multiple β_3 is still expected to pick this up. If $\kappa_h \neq 0$ [$h = 11, 22, 33$ and 13], all earnings valuation coefficients will be affected by other VAR coefficients. In particular, they will be positively related to the accounting conservatism parameters κ_{14} and κ_{15} identified in previous research by Feltham and Ohlson (1995), Pope and Wang (2005), and Clubb (2013).

Similarly, the valuation model in equation (6) can be rewritten in terms of normal earnings components consistent with the abnormal earnings representation in equation (4) using the clean surplus and core abnormal earnings definitions:

$$MV_t = \beta_1^* ce_t + \beta_2^* trte_t + \beta_3^* sce_t + \beta_4^* bv_t + \beta_5^* dv_t \tag{7}$$

where the implied valuation multiples are;

$$\beta_1^* = \beta_1 R = \frac{R[\kappa_{11}(R-\kappa_{44}) + \kappa_{14}\kappa_{41}]}{\vartheta}$$

$$\beta_2^* = \beta_2 + \beta_1(R-1) = \frac{R\left[\kappa_{14}(\kappa_{42} + \kappa_{41}(R-\kappa_{22}-1)) + (R-\kappa_{44})(\kappa_{22} + \kappa_{11}(R-\kappa_{22}-1))\right]}{\vartheta(R-\kappa_{22})}$$

$$\beta_3^* = \beta_3 + \beta_1(R-1) = \frac{R\left[\kappa_{14}(\kappa_{43} + \kappa_{41}(R-\kappa_{33}-1)) + (R-\kappa_{44})(\kappa_{13} + \kappa_{33} + \kappa_{11}(R-\kappa_{33}-1))\right]}{\vartheta(R-\kappa_{33})}$$

$$\beta_4^* = \beta_4 - \beta_1(R-1) = \frac{R\left[\kappa_{14} - \kappa_{14}\kappa_{41} - (R-\kappa_{44})(\kappa_{11}-1)\right]}{\vartheta}$$

$$\beta_5^* = \beta_5 + \beta_1(R-1) = \frac{\kappa_{14}(\kappa_{41} + \kappa_{45} - \kappa_{41}R) + (R-\kappa_{44})(\kappa_{11} + \kappa_{15} - \kappa_{11}R)}{\vartheta}$$

To differentiate between the valuation models in equations (6) and (7), we call the valuation model in equations (6); a core abnormal earnings valuation model $(CAE-MODEL)$ and the valuation model in equation (7); a core earnings valuation model $(CE-MODEL)$.

When considering the theoretical values of the forecasting and valuation coefficients of both ce_t and sce_t in equations (4), (6) and (7) in terms of their κ values, our analysis provides a link between a direct and indirect forecasting and valuation roles of sce_t. To elaborate on this point, consider the difference between the total abnormal earnings forecasting coefficients of ce_t and sce_t in equation (4):

$$\delta_3 - \delta_1 = \kappa_{13} + \kappa_{33} - \kappa_{11} \tag{8}$$

Equation (8) shows that if $\kappa_{13} + \kappa_{33} = \kappa_{11}$, the forecasting relevance of shifted core earnings sce_t in relation to future total abnormal earnings will be identical to the forecasting relevance of reported core abnormal earnings ce_t (because $\delta_3 - \delta_1 = 0$). Indeed, this is what one would expect if the presence of shifting behavior by the manager does not itself provide a signal of future performance. This is because the impact of sce_t on next period total abnormal earnings is equal to its impact on next period reported core abnormal earnings, κ_{13}, *plus* any association between shifted earnings at date t and shifted earnings at date $t+1$ via κ_{33}. Therefore, if $\kappa_{13} + \kappa_{33} > \kappa_{11}$, this implies that the forecasting relevance of shifted earnings is greater than reported core earnings, consistent with the notion that shifting core losses into transitory items signals managerial incompetence and even lower future abnormal earnings and hence is a bad news signal.[7]

Turning now to the equivalence of this condition in the valuation models, the difference between the valuation multiples for ce_t and sce_t is as follows:

$$\begin{aligned}\beta_3^* - \beta_1^* &= \beta_3 - \beta_1 \\ &= \frac{R\left[(\kappa_{13} + \kappa_{33} - \kappa_{11})(R - \kappa_{44}) - \kappa_{14}(\kappa_{41} - \kappa_{43})\right]}{(R - \kappa_{33})\left[(R - \kappa_{11} - \kappa_{15})(R - \kappa_{44}) - \kappa_{14}(\kappa_{41} + \kappa_{45})\right]}\end{aligned} \tag{9}$$

The difference in equation (9) equals zero under the requirement that $\kappa_{13} + \kappa_{33} = \kappa_{11}$, given an additional condition that $\kappa_{41} = \kappa_{43}$. In relation to the plausibility of the latter condition, one can substitute the CSR requirements $\kappa_{11} = \kappa_{51} + \kappa_{41}$ and $\kappa_{13} = \kappa_{53} + \kappa_{43} - \kappa_{33}$ into $\kappa_{13} + \kappa_{33} = \kappa_{11}$ which implies that $\kappa_{51} = \kappa_{53}$ if $\kappa_{41} = \kappa_{43}$. In other words, the additional condition that $\kappa_{41} = \kappa_{43}$

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[7] As mentioned earlier, we consider shifting negative core earnings to transitory earnings, hence sce_t is negative by construction.

can be interpreted as simply requiring the expectations of future dividend payout not to be affected by the division of core (abnormal) earnings between reported and shifted earnings. Clearly, if the book value equation in the VAR has been restricted such that only κ_{44} affects future book value as in Feltham and Ohlson (1995) and Barth et al. (1999b), one needs not to assume any further condition in order for $\kappa_{13}+\kappa_{33}=\kappa_{11}$ to results in $\beta_3-\beta_1=0$[8]. Alternatively, if $\kappa_{14}=0$, then $\beta_3-\beta_1=0$ when $\kappa_{13}+\kappa_{33}=\kappa_{11}$ even if $\kappa_{41}\neq\kappa_{43}$. Therefore, the condition $\kappa_{13}+\kappa_{33}=\kappa_{11}$ is fundamental to the equivalent valuation of reported and shifted core earnings.

The total abnormal earnings dynamic in equation (4) shows that the direct effect of sce_t may also be augmented by an indirect (signalling) effect if shifting provides a bad news signal to the market about future total abnormal earnings, I.e. $\kappa_{13}+\kappa_{33}>\kappa_{11}$. In an efficient market, equation (9) indicates that the bad news effect is expected to result in a higher valuation of shifted core earnings.

To summarize, our model setup assumes an accounting system that accommodates a hypothesized earnings variable sce_t which represents misclassified core earnings in the income statement. Restrictions applied on the VAR transition matrix indicate how each component of earnings impacts on the total abnormal earnings dynamic and the valuation models. The analysis shows possible direct and indirect forecasting and valuation effects for sce_t that are consistent with the view that shifted core earnings contain useful information both as core earnings and possibly as a signal of firms that attempts to opportunistically maximize their reported performance.

The total abnormal earnings dynamic in equation (4) and the valuation models in equations (6) and (7) form the basis of our empirical tests. We also consider estimating the VAR and calculating the theoretical counterparts of the coefficients in these equations as per our theoretical analyses.

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[8] Empirically, we show that calculating $\beta_3-\beta_1$ when the book value equation has all coefficients restricted to zero except κ_{44} do not change inferences.

3. Constructing a Measure of Shifted Core Earnings

Special items have been broadly considered an objective measure of transitory earnings (Burgstahler et al. 2002, Frankel 2009, and Christensen et al. 2011). Hence, the identification of core and transitory earnings is readily available to investors in the income statement. However, to test the model predictions we need a measure of the core portion of special items[9]. Prior empirical research (Ronen and Sadan, 1975 and Barnea, et al. 1976) posits that an association between deviations of core earnings and transitory items from their expected levels is evidence of classificatory smoothing. These studies assume that transitory earnings are expected to be constant, should no income smoothing occur. This assumption is deemed to be restrictive and unrealistic, because it explicitly assumes consistent recurrence of non-recurring items. McVay (2006) avoids estimating a transitory earnings expectation model, and assumes that a contemporaneous association between unexpected core earnings and negative special items level documents the presence of classification shifting. Nevertheless, none of these studies attempt to identify a misclassified core earnings component that is part of transitory earrings.

In this current paper, we focus on shifting operating expenses to negative special items because there is more supporting empirical evidence for shifting expenses than revenues. Therefore, the earnings variable sce_t represents shifted (negative) core earnings and the earnings variable $pute_t$ implies purified special items[10]. Since sce_t is a misclassified core earnings component in this current setting and core earnings are more tractable than transitory earnings, our approach to estimate sce_t is based on constructing a measure of shifted negative core earnings that is firm-industry specific and is updated annually. The basic idea is that a fraction of negative special items is in essence negative core earnings that have been moved from core

[9] Most empirical research estimating different components of earnings where some of them are unobservable follow certain assumptions to define the unobservable components of earnings. For example, dirty surplus earnings are measured using a clean surplus relation that has two earnings components: core earnings and dirty surplus in Ashton and Wang (2013), while they are directly observable in Landsman et al., (2011) who assume that really dirty surplus are those dirty surplus earnings not observed by investors. Landsman et al., measure the really dirty surplus component using a more comprehensive variant of the clean surplus relation. Another measurement approach of unobservable earnings components appears in the earnings management literature when estimating the discretionary and nondiscretionary elements of total accruals. To the extent that all estimation methods might measure the unobservable variables of interest with error, misspecification of the measurement model is always an alternative interpretation of the empirical results.

[10] We will also consider purified *negative* special items in our empirical tests.

earnings to negative special items when misclassification takes place. Hence sce_t for firm i at year t is measured as:

$$sce_{it} = \chi(negsi_{it}) \tag{10}$$

where $negsi_{it}$ is negative special items for firm i at year t.

To estimate χ, there has to be ex ante evidence of classification shifting, and a mechanism through which one can *extract* the ratio of shifted negative core earnings. In prior literature, this type of classification shifting is tested using the following OLS regressions in McVay (2006):

$$[ce_{it} - E(ce_{it})] = \omega_0 + \omega_1 negsi_{it} + error_{i,t} \tag{11}$$

$$[\Delta ce_{i,t+1} - E(\Delta ce_{i,t+1})] = \phi_0 + \phi_1 negsi_{it} + error_{i,t+1} \tag{12}$$

where $E(ce_{i,t})$ is expected core earnings level and $E(\Delta ce_{i,t})$ is expected core earnings change and are measured using the following empirical models:

$$ce_t = \eta_0 + \eta_1 ce_{t-1} + \eta_2 ato_t + \eta_3 acc_{t-1} + \eta_4 acc_t + \eta_5 \Delta sa_t + \eta_6 neg\Delta sa_t + error_t \tag{13}$$

$$\Delta ce_t = \theta_0 + \theta_1 ce_{t-1} + \theta_2 \Delta ce_{t-1} + \theta_3 \Delta ato_t + \theta_4 acc_{t-1} + \theta_5 acc_t + \theta_6 \Delta sa_t + \theta_7 neg\Delta sa_t + error_t \tag{14}$$

where ce_t is core earnings level (scaled by sales), Δce_t is core earnings change (scaled by sales) ato_t is the asset turnover ratio, acc_t is operating accruals (scaled by sales), Δsa_t is the percentage change in sales, and $neg\Delta sa_t$ is sales decrease which is equal to Δsa_t if Δsa_t is negative, and 0 otherwise.

Estimates are made out of sample using coefficients from equations (13) and (14) estimated by fiscal year and industry and excluding firm *I*. In normal operations, negative special items are meant to be a sign of poor performance which is supposed to create a negative relation between unexpected core earnings and negative special items (a performance effect). However, when a firm shifts negative core earnings at time t to negative special items, unexpected core earnings will *increase* with negative special items at time t, I.e. $\omega_1 > 0$.[11] At time $t+1$, this improvement in core earnings *reverses* as negative core earnings shifted at time t recur, I.e $\phi_1 < 0$. However, the reversal will be less pronounced in case of inter-period shifting and nearly zero if a firm has special items at time $t+1$, because of the possibility of serial misclassification.

In order to extract the ratio of shifted negative core earnings within special items; first, we estimate ω_1 per industry and year if there are more than 15 observations per the industry-year combination. As shown later, this will result in *positive* and *negative* values of ω_1 that differ among industries in the same year and for the same industry over years. The intuition is that in a given year, not all firms in the sample misallocate core expenses and if some firms do, they might not persistently classification-shift in all future years. Hence, an estimate of $\hat{\chi}$ that is updated annually is as follows:

$$\hat{\chi}_{ind\ t} = \omega_{1,ind\ t} \tag{15}$$

We set $(-)\omega_{1,ind\ t} = 0$, because those are not classification shifters; and $\omega_{1,ind\ t}(>1) = 0$, because these coefficients are outliers[12]. Second, we multiply the estimate of $\hat{\chi}$ for each firm industry-year combination by the firm's actual negative special items. This results in a firm industry-specific estimate of shifted negative core earnings each year that is within the bound of shifting such that $[sce_{i,t} = \hat{\chi}_{ind,t}(negsi_{i,t})]$, where $1 > \hat{\chi}_{ind\ t} > 0$. We also estimate purified special items as the difference between reported special items and our measure of sce_t. This ensures that $pute_t$ becomes equal to reported special items when firms do not classification shift (I.e. when there is no shifting in the current year, $\hat{\chi}_{ind\ t} = 0 \rightarrow sce_t = 0$ and $pute_t = te_t$) .

The estimation of other variables is straightforward; core earnings variable ce_t is measured as (sales – cost of goods sold – selling, general and administrative expenses) similar to McVay

[11] Assuming negative special items are measured at their absolute values here consistent with McVay (2006).

[12] It does not make sense for a firm to have more than 100% of its negative special items as shifted core expenses, because classification shifting is bounded by the amount of negative special items. We believe it is more conservative to disregard these coefficients (substituting by 0) rather than assuming 100% shifting. Even if we set these coefficients to 100%, inferences do not change.

(2006), Barua et al. (2010) and Fan et al (2010). We measure bv_t as book value of common equity at the end of the fiscal year and dv_t as common dividends declared. We set $R = 1.12$ (Dechow et al. 1999, Hand and Landsman 2005 and Barth et al. 1999b), therefore the core abnormal earnings variable is estimated as ($cae_t = ce_t - 0.12 \times bv_{t-1}$). Total abnormal earnings $(ae_t = e_t - 0.12 \times bv_{t-1})$ are measured using two measures of income; ae_t^{ni} where $e_t = e_t^{ni}$ is net income, and ae_t^{ib} where $e_t = e_t^{ibc}$ is income before extraordinary items and discontinued operations[13]. We measure MV_t as market value of equity three months after the end of the fiscal year. Since estimating sce_t is based on regressions in McVay (2006) where sales are used as the deflator for most variables, we deflate other variables in the VAR, forecasting and valuation models by sales for consistency. Detailed definitions of all variables and their locations in datasets are provided in appendix.

4. Data and Sample Selection

We collect accounting data from annual Compustat and stock prices from the monthly Center for Research in Security Prices (CRSP) for years 1989 through 2012. We start our sample in 1989, because accruals are measured directly from the cash flow statement, and cash flow from operations are reported in Compustat after 1988[14]. All variables are measured as of fiscal year-end, except equity market values which are measured three months after the end of the fiscal year from which financial statements data are gathered to ensure that financial statements are in the public domain.

We follow McVay (2006) in our initial sample selection procedures. Each firm-year observation is required to have sufficient data to estimate the core earnings level and change models and shifted core earnings. We drop observations with sales less than $1 million as sales are used as a deflator for most variables in the regressions. We also drop firms that have changed their fiscal year end between $t-1$ and t. Two-digit SIC code is used to identify industry membership. We require a minimum of 15 observations per industry-year combination in all industry level

[13] We refer to the implication of these measures on our estimation when we report the abnormal earnings estimation results.

[14] Hribar and Collins (2002) find that accruals are measured with error, when they are estimated as the change in subsequent balance sheet accounts.

regressions. We assign 0 to special items if the data item is missing (Elliott & Hanna 1996 and Dechow and Ge 2006), or the special items are positive (McVay 2006)[15]. Also, extraordinary items and discontinued operations used to calculate accruals in the core earnings models are set to 0 if the data item is missing. We do not limit estimation of sce_t to firms with full data for the forecasting-valuation models and all abnormal earnings specifications, because doing so would unnecessarily limit the generalizability of the shifted core earnings measure (Barth et al. 1999a). This results in a sample of 69,430 firm-years used to estimate sce_t. In tests of the forecasting-valuation systems, we further delete observations with missing book value and dividends and the net income measure of abnormal earnings. Cost of capital is assumed to be constant at 0.12 consistent with most similar studies. All variables used in regressions are winsorized at their first and ninety-ninth percentiles. The final sample used to estimate the forecasting-valuation equations is 54,912 firm years.

5. Empirical Results

5.1 Shifted Core Earnings Estimation Results

We begin our empirical analysis by replicating the classification shifting tests in McVay (2006), in order to investigate if firms tend to shift negative core earnings to negative special items, on average, in our sample. Table 1 Panel A reports the results of pooled OLS and quintile regressions for the core earnings level model in equation (13) and Table 1 Panel B provides the regression results for the core earnings change model in equation (14). Table 1 Panel A and B also report summary statistics for mean and median coefficients from industry-year regressions. Results indicate that all coefficients are statistically significant and have the predicted sign as in McVay (2006). Both pooled and industry-year mean and median coefficients values in Table 1 are consistent with their values in McVay[16].

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[15] Though Compustat reports special items on a net basis which implies that negative special items reported in Compustat are the outcome of netting both positive and negative special item sub-types, Johnson et al. (2011) find that when a firm reports a negative special item, the special item sub-types are almost always negative. Since Compustat starts only to report the breakdown of special items in 2001, we measure negative special items as net income decreasing special items as reported by Compustat (Data item #17), if it is negative, and zero otherwise.

[16] McVay(2006) reports the mean and median coefficients from regressions estimated by industry (using Fama and French (1997) industry classification) and fiscal year, and one tailed p-values in her tables 4 and 5. In Table 1 Panel

[Insert Table 1 here]

In order to test for the presence of classification shifting as per equations (11) and (12), we run OLS regressions and report the significance of regression coefficients using two-way clustered standard errors, with firm and year clusters (Petersen 2009, Gow et al, 2010). Negative special items are measured at their absolute values here, in order to be consistent with McVay when we report our results in this section. We do not require next year unexpected change in core earnings to be non-missing to avoid the selection bias.

Table 2 Panel A provides the regression results for equation (11). Results reveal that unexpected core earnings are increasing with negative special items at time t , which is consistent with classification shifting rather than a poor performance effect associated with negative special items reporting. The coefficient on $negsi_t$ is positive and significant at the 0.01 level ($\omega_1 = 0.042$, t = 2.81). This means that approximately 4.2 % of reported negative special items, on average, are operating expenses that were shifted from core earnings in the current year. A one standard deviation increase in negative special items as a percent of sales results in an average increase of 38 basis points ($\omega_1 \times sd_{negsi}$) in unexpected core earnings.

Table 2 Panel B provides the regression results for equation (12). Results reveal that the coefficient on negative special items is negative and significant at the 0.01 level ($\phi_1 = -0.034$, t = −2.80). This implies that the improvement in core earnings reverses in the next year, because previously misclassified operating expenses recur. The reversal is 31 basis points ($\phi_1 \times sd_{negsi}$) for a one unit increase in negative special items as a percent of sales. As indicated by McVay, inter-period shifting may decrease the reversal. In untabulated results, we find that the reversal is not statistically different from zero when firms reports negative special items in year $t+1$[17]. This is not surprising because firms can continue to misallocate operating expenses when they have

A and Panel B, we show the pooled mean and median regressions results and summary statistics for mean and median coefficients from the industry year regressions used to estimate core earnings levels and changes. Both pooled and industry-year coefficients values are very close to those in McVay. Industry-year regressions have higher explanatory power. In our estimation of core earnings levels and changes, we follow the same approach as in McVay, in order to calculate unexpected core earnings, i.e. expectations are made out of sample from industry-year regressions excluding firm i .

[17] When we add negative special items at year t+1 to the regressions and restrict that they are not equal to zero, the coefficient on current year negative special items is −0.0129 and not statistically different from zero.

consecutive special items. For these reasons, in constructing our measure of shifted core expenses, we focus on firms that classification shift each year, regardless of whether the shift reverses in the next period.

In sum, the results suggest that an *average* percentage of 4.2 of negative special items reported by firms represent operating expenses (a core earnings component) that were opportunistically shifted to negative special items (a transitory earnings component). Since, our sample has some overlap with the $1988-2003$ sample period used in McVay, these results confirm her principal findings for classification shifting using recent data.

This approximate ratio does not imply that all negative special item firms are classification shifters to some degree. Therefore, in order to estimate a more accurate measure of the ratio of misallocation, we rerun equation (11) for each industry-year combination and estimate industry specific coefficients that are updated annually. This results in a range of positive and negative ω_1 each year. As indicated before, we set all $(-)\omega_{1,ind\ t}$ to equal 0 (representing 46 % of estimated $\omega_{1,ind}$) because those are not classification shifters and are more likely reporting negative special items as result of poor performance . In addition, $\omega_{1,ind\ t} > 1$ are set to equal 0 (representing only 3.91 % of estimated $\omega_{1,ind\ t}$), as we believe that those are outliers. The post-restriction coefficients represent the annual measure of χ. In order to estimate shifted negative core earnings at the firm-year level, we multiply the industry measure by actual negative special items reported by each firm in a given industry. The use of two-digit SIC codes provides a more spread pattern of estimated coefficients than the Fama-French 48 industry classification, which is more relevant to this study, because the aim is to estimate coefficients that are more specific to each industry *smaller* group.

[Insert Table 2 here]

In Figure 1 Panel A, we report on the time series of unexpected core earnings surrounding our shifting measure, an *average* measure of shifting based on the fitted value from a pooled OLS regression of unexpected core earnings on negative special items, and a *control* firms' industry measure that is based on only the excluded *negative* coefficients from our measure of shifting and estimated in a similar fashion as the treatment firms comprising the shifting measure (I.e.

control firms are those experiencing current poor performance rather than shifting). Year zero is the event year of a non-zero value of the measures, and the plots show the means of unexpected core earnings for three years prior to and subsequent to the event year. The figure shows that our shifting measure captures the spirit of McVay's classification shifting construct better than an average measure of shifting. According to our shifting measure, there is a substantial improvement in unexpected core earnings in the year of shifting, and this improvement is followed by a monotonic decline consistent with firms' inability to maintain the temporary improvement in unexpected core earnings. For example, unexpected core earnings are negative and zero in year $t-2$ and year $t-1$, respectively, markedly increase above zero in the year of shifting, and then monotonically decrease for three years following the year of shifting (reversal). This is consistent with McVay (2006) and our regression results in Table 2. While such pattern is consistent with classification shifting, it is much less pronounced using an average measure of shifting that combines both shifters and poor performers. For the poor performance control measure, unexpected core earnings substantially decline when firms report negative special items as a result of low performance at year zero, and this decline is followed by an increase that lasts for two years. This is consistent with future performance-enhancing in the short term after recognition of negative special items as one would expect when negative special items are not used for shifting purposes.

In Figure 1 Panel B, we show, based on our shifting measure, the differential temporal patterns of unexpected core earnings when shifting occurs at the event year, as in Panel A, and when firms serially shift in both year zero and year $t+1$. Serial shifters experience higher level of unexpected core earnings in year zero and even improve it in year $t+1$, when they shift again. This is later followed by a monotonic decline in performance that documents their failure to maintain the artificial improvement in performance in the years subsequent to the shift. Indeed, this is consistent with the non-reversal result in the unexpected core earnings change regression when the sample is restricted to firms that shift in years t and $t+1$ as in McVay (2006). Overall, these observations add credibility to the extraction approach we use in isolating shifted core expenses from negative special items, and are consistent with the shifting mechanism documented in prior research.

We now move on to report annual changes in negative special items and shifted negative core earnings based on our measure. Figure 2 shows the annual trend of reported negative special items and the estimated core component (shifted negative core earnings) in the sample. Figure 2 panel A indicates that the frequencies of firms reporting negative special items and misclassifying negative core earnings have dramatically increased over the sample years. In 1991, 25% of all firms reported negative special items and 8% of all firms shifted negative core earnings to negative special items. By 2012, the frequency of negative special items firms increased to approximately 52%, while 30% of the sample firms engaged in classification shifting. Focusing on only negative special items firms, Figure 1 Panel B indicates that the incidence of shifting for negative special items firms increased from approximately 34% to 55%, while peaking at 80% in 2008 during the financial crisis period. Overall, this descriptive evidence is consistent with an increasing number of firms reporting negative special item and misallocating expenses over the sample period.

Figure 3 shows how the magnitude of negative special items and shifted negative core earnings changed over time. In Panel A, we show the annual trend of the absolute value of negative special items, conditional on the firm reporting negative special items. The magnitude of negative special items has increased over years from 25 million to approximately 43 million, while peaking at approximately 79 million during the financial crisis period in 2008. In Panel B, we show the means of negative special items scaled by sales, as used in regressions, conditional on the firm reporting negative special items; and shifted negative core earnings, conditional on the firm misallocating the expense. The magnitude of negative special items as a percent of sales increased from 1991 to 2002 (ranging between 7% to 10%). After 2002, the ratio decreased dramatically over the sample period (from 10% in 2002 to 3% in 2012); however, in 2008 it increased to approximately 11%. With respect to our estimates of shifted negative core earnings, the mean remained relatively stable over the years in our sample.

[Insert Figure 1 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

5.2 Summary Statistics

Table 3, Panel A presents distributional statistics for the main variables used in the forecasting and valuation models. The mean core earnings are higher than mean negative special items and shifted negative core earnings. Consistent with Barth et al. (1999b) mean abnormal earnings calculated using net income or income before extraordinary items and discontinued operations is negative. This could be attributable to the profitability of firms, on average, is less than the required cost of capital or that the assumed constant cost of capital of 12% used in calculating abnormal earnings is too high. However, using book value in the abnormal earnings dynamic mitigates the problem of a fixed cross sectional cost of capital.

Table 3 Panel B reports Pearson and Spearman correlation coefficients for the main explanatory variables in the forecasting and valuation models. All correlation coefficients are statistically significant but their magnitudes do not raise collinearity concerns. In general, none of the correlation coefficients exceeds 0.5 except the correlation between $pute_t$ and sce_t which is close to 0.6. However, in subsequent regressions, variance inflation factors for all explanatory variables are less than 10 (Kennedy 1992).

[Insert Table 3 here]

5.3 The Vector Autoregression Results and Implied Theoretical Values of Forecasting and Valuation Coefficients

We estimate all forecasting and valuation regressions using fixed effects panel data models except for regressions with truncated dependent variables where we use censored regressions with fixed effects. We start with estimating the κ matrix of the VAR in order to calculate the theoretical counterparts of the total abnormal earnings dynamic and valuation models coefficients. Though we mainly draw our conclusions regarding the forecasting and valuation properties of z variables based on the coefficients of the total abnormal earnings and valuation models in next sections, which are estimated using unrestricted regressions, the implied theoretical values serve as benchmarks for these coefficients.

Table 4 Panels A and B show the estimates of the κ matrix coefficients and the implied theoretical values for the forecasting and valuation models coefficients based on these estimates.

Table 4 Panel A reveals that all variables are statistically significant in all VAR equations except dv_t in the book value equation. The core abnormal earnings equation results show that future core abnormal earnings are positively associated with current core abnormal earnings ($\kappa_{11} = 0.316$), shifted negative core earnings ($\kappa_{13} = 0.225$) and dividends ($\kappa_{15} = 0.312$) and negatively associated with current book value ($\kappa_{14} = -0.145$). Since sce_t is a negative variable, by construction, we interpret this as firms that shift operating expenses to negative special items in the current period in order to temporarily increase current reported core earnings will have lower core abnormal earnings in the next period. This is also consistent with our results in Table 2 and McVay (2006) where shifted operating expenses revert back to core earnings in the future. In economic terms, a one standard deviation increase in operating expenses that are packed into special items results in approximately 21 basis points $\left(\kappa_{13} \times \mathrm{SD}_{sce} = 0.225 \times 0.009\right)$ decrease in core abnormal earnings in the next period (all scaled by sales).

The purified transitory earnings equation results show that purified special items exhibit negative persistence in a small magnitude $(\kappa_{22} = -0.044)$. This suggests that current purified special items' gains and losses partially reverse in the next period. Jones and Smith (2011) observe a similar negative autoregression for reported special items (albeit insignificant in their analysis using a different persistence test approach) that continues for two lags. The shifted core earnings equation indicates that our measure of operating expenses that are misrepresented as negative special items in the income statement exhibits a positive autoregression $(\kappa_{13} = 0.166)$. This indicates the persistent trend of shifting and implies that one dollar shifted to special items in the current period is associated with less than a dollar in the next period[18].

The book value equation results show that next period book value is high, when current period book value, core abnormal earnings and purified special items are high; while it is only marginally affected by shifted negative core earnings (at the 10% level), and not affected by dividends paid. Indeed, our theory demonstrates that a perfect theoretical linkage between differential forecasting and valuation properties of ce_t and sce_t occurs when $\kappa_{14} = 0$ or

[18] Since we measure sce_t each year from the contemporaneous relation between unexpected core earnings and negative special items, the positive autoregression here is more consistent with a persistent trend of shifting than an inter-period shifting practice.

$\kappa_{41} = \kappa_{43}$, which we do not obtain empirically herein. Another theoretical constraint that leads to the same forecasting-valuation link is not to allow earnings variables to forecast future book value. Therefore, we also re-estimate the book value equation as a simple autoregression process and do not allow feedback from other variables (Feltham and Ohlson 1995). The book value autoregression coefficient κ_{44} is approximately the same in this case. When we calculate the theoretical counterparts of the coefficients of the total abnormal earnings dynamic and valuation models in Table 4 Panel B, we consider different alternatives based on our estimation of the book value equation, in order to see how binding this variables-exclusion restriction is. The dividends equation results show that future dividends are positively associated with all VAR variables.

Table 4 Panel B reports the calculated theoretical counterparts of the total abnormal earnings dynamic and the valuation models coefficients that are based on our estimation of the VAR transition matrix, κ. We add " ` " to the calculated theoretical coefficients to differentiate them from their observed values in the regressions that we estimate in the following sections. All calculated forecasting coefficients in the $AE - DYNAMIC$ are as one would expect according to our theoretical analysis. Core earnings and shifted negative core are expected to forecast total abnormal earnings, while purified special items appear to have a very weak theoretical forecasting ability. This validates our theoretical VAR setup and measurement approach for sce_t, and ensures that special items should have less forecasting power, if one appropriately extracts the permanent composition attributable to classification shifting. The difference between ce_t and sce_t theoretical forecasting abilities result, $\delta_3` - \delta_1` = 0.075$, is attributable to the result that $\kappa_{11} < \kappa_{13} + \kappa_{33}$. This leads us to expect that sce_t may have dual forecasting roles, a core earnings variable and a bad news signal. The theoretical effects of book value and dividends on future total abnormal earnings $(\delta_4` = -0.183, \delta_5` = 0.274)$ are consistent with their feedback on core profitability in the first equation of the VAR.

With regard to valuation, we calculate three variants of the theoretical counterparts of the $CAE - MODEL$ and $CE - MODEL$ valuation coefficients using all significant and insignificant κ coefficients, only significant κ coefficients at least at the 5% level (i.e. further setting

$\kappa_{43} = 0, \kappa_{45} = 0$), and lastly when future book value is only affected by current book value and no feedback is assumed from other variables (I.e. $\kappa_{41} = 0,\ \kappa_{42} = 0,\ \kappa_{44} = 0.527,\ \kappa_{43} = 0,\ \kappa_{45} = 0$). In the last column, we report the means of the theoretical values based on these three variants. Overall, our results confirm that differences between calculated coefficients under these alternatives are minor, and they all lead to similar conclusions with respect to the valuation properties of the variables. The results for both valuation models show that core abnormal earnings, core earnings and shifted negative core earnings have theoretical valuation coefficients higher than purified special items. Consistent with the abnormal earnings dynamic results, shifted negative core earnings provide superior valuation information to core abnormal earnings as if they serve dual roles ($\beta_3^{*`} - \beta_1^{*`} = \beta_3` - \beta_1` = 0.344$). The valuation results here ensure that allowing coefficients from the specific dynamic processes of book value and dividends in the fourth and fifth rows of the VAR to vary leads to similar earnings valuation coefficients. Purified special items continue to have smaller and negative theoretical valuation coefficient relative to other earnings variables in both valuation models. However, though the theoretical forecasting coefficient of purified special items is small and near to zero ($\delta_2` = -0.006$), their theoretical valuation coefficient is somewhat higher ($\beta_2^{*`} = [-0.083\ ,\ -0.02]$). This suggests that purified special items provide some useful information in valuation despite having lower forecasting ability due to their partial reversal in the future as noted here. Indeed, this valuation role is consistent with Callen et al. (2010) who find empirical evidence that conditional conservatism is facilitated via special items, hence special items are priced by the market as a tool through which conservatism is achieved though their transience. More importantly, the results show a very clear link between forecasting and valuation for core earnings and its shifted portion to special items, such that $\kappa_{11} < \kappa_{13} + \kappa_{33}$ in the estimated VAR leads numerically to $\delta_1` < \delta_3`$ and $\beta_1` < \beta_3`$.

[Insert Table 4 here]

5.4 The Abnormal Earnings Dynamic Results

5.4.1 Main Results

Our formulation for the VAR provides the theoretical foundations for our predictions and tests regarding forecasting and valuation properties of the core and transitory components of reported special items. We restricted specific κ coefficients to be equal to zero consistent with theory and the VAR empirical results appear to support the main theme of classification shifting. Moreover, the calculated theoretical counterparts of the abnormal earnings dynamic and valuation models coefficients show that the shifted negative core earnings coefficient is higher than the core earnings coefficient, and both coefficients are higher than the purified special items coefficient. Nevertheless, our results so far are still limited by the assumption of the VAR as the data-generating process for the underlying variables.

The advantage of estimating the $AE-DYNAMIC$ directly is that the corresponding empirical results will not be based on any assumptions in the VAR with regard to the evolution of the variables and will show the differential forecasting ability of each earnings component in presence of other earnings components in the regression. Moreover, we can use different variants of the abnormal earnings regression to test our predictions, such as replacing purified special items with only purified negative special items, aggregating the two components of special items into reported special items, and decomposing core earnings into positive and negative components hence reported negative core earnings are directly compared with shifted negative core earnings. It worth noting that even if no restrictions are applied on the VAR transition matrix, we will end up with a similar regression for the $AE-DYNAMIC$ except that the "theoretical" values of the coefficients will depend on the full interaction of variables. Therefore, estimating the abnormal earnings dynamic as an unrestricted regression is expected to provide evidence on the validity of our measure of sce_t and our specific characterization of the founding VAR.

In our tests for the dynamic and valuation models, we admit that these functions are abstracts from many fundamental issues that might affect expectations and valuation. For example, the models suppress non-accounting information and other unobservables which, if correlated with the regression variables, would cause omitted variable bias. Estimating the models more precisely might require separation of the ordinary error term and those unobservables. Therefore, we begin by reporting the estimated coefficients of the dynamic using an ordinary least square (OLS) as a benchmark, in addition to other estimators. Though results in relation to the main test of whether shifted negative core earnings can forecast one year ahead abnormal earnings are consistent, further tests favor a panel fixed effects model.

We estimate the abnormal earnings dynamic in Table 5. In Panel A, we start by estimating the dynamic using a net income measure of abnormal earnings, ae_{t+1}^{ni}, consistent with theory that abnormal earnings are to be calculated using a clean surplus measure of earnings. In Panel B, we follow prior research that uses an income before extraordinary items and discontinued operations measure of abnormal earnings, ae_{t+1}^{ib} (Dechow et al. 1999, Tsay et al. 2008). Though this latter measure violates clean surplus, it builds on an empirical perspective that extraordinary earnings and discontinued operations are nonrecurring items that should be excluded from the abnormal earnings measure. In Panel C, we use a more cautious approach, that is driven by theory, to deal with the dynamic and the clean surplus relation by including another explanatory earnings variable calculated as the difference between the earnings measure used for estimating abnormal earnings on the LHS and all other earnings components used in the RHS of the regression. Specifically, we include an earnings "plug" variable, ni_plug, equal to (net income − core earnings − special items) in the abnormal earnings dynamic that uses net income as a measure of abnormal earnings. We also consider a similar variable, ib_plug, equal to (income before extraordinary items and discontinued operations − core earnings − special items) in the abnormal earnings dynamic that uses income before extraordinary items and discontinued operations in the abnormal earnings measure. We scale the "plug" variables by sales to be consistent with other variables in the analysis.

In Panel A, the OLS results show that all earnings components have significant coefficients in the dynamic. The differences in forecasting weights among earnings variables is "eye catching"[19]. Overall, the coefficients on earnings components are significantly different from

[19] Only Wald test statistics relating to the differential forecasting and valuation relevance between core earnings and shifted negative core earnings are reported in the tables. All other Wald test results are reported in the text.

one another $[F = 54.80, p = 0.00]$.The forecasting coefficient on core earnings is significantly positive $(\delta_1 = 0.727)$, and indistinguishable from the forecasting coefficient on shifted negative core earnings $(\delta_3 = 1.218)$ [$F = 2.01, p = 0.1566$]. The forecasting coefficient on purified special items is statistically significant $(\delta_2 = 0.274)$, but smaller than core earnings and the difference is significant [$F = 101.30, p = 0.00$]. Results do not change when the dynamic is estimated using Fama−Macbeth cross-sectional regressions[20].

The results of both the random and fixed effects models lead also to rejection of equality of coefficients on earnings components in forecasting one year ahead abnormal earnings $[\text{Random}: \chi^2 = 697.76, p = 0.00, \text{Fixed}: F = 194.37, p = 0.00]$. In both models, core earnings act as a strong predictor of future abnormal earnings and shifted negative core earnings are statistically significant at the 0.01 level with slightly higher coefficients than core earnings. Wald test results show that this differential forecasting ability in favor of shifted core earnings is statistically insignificant across all estimations. Comparing random effects with fixed effects models, we obtain a Hausman test statistic of 324.195 $(p = 0.000)$ that is heteroscedastic and firm cluster-robust, suggesting that unobservables are correlated with regressors and a fixed effects model is a better choice for estimating the dynamic over a random effects model. Though, main conclusion regarding the forecasting relevance of shifted negative core earnings does not change, we base our main analysis on fixed effects[21].

Interestingly, the fixed effects model reveals that the coefficient on purified special items is not statistically different from zero $(\delta_2 = 0.011)$ as predicted by theory[22]. This result ensures the existence of unobservables that are caught up by the error term in the pooled OLS and are swept out by the fixed effects technique. Shifted negative core earnings persist to have a forecasting

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[20] *t*-statistics are computed using the Newey-West (1987) correction for heteroscedasticity and autocorrelation. We use a lag of two in the Newey-West procedure; however untabulated results show that significance is not sensitive to a higher lag length.

[21] Johnsons et al. (2011) find that there are significant differences across industries in the propensity to report special items and that industry effects must be controlled for in any analysis that include special items. We believe that using a panel fixed effects model controls for this heterogeneity at a higher level (firm fixed effects).

[22] The predicted coefficient for purified special items is near to zero and negative. Table 5 Panel A shows a small positive coefficient that is indistinguishable from zero. When we change our abnormal earnings income measure to exclude extraordinary items and discontinued operations in Table 5 Panel B, we obtain the exact negative coefficient that is indifferent from zero.

coefficient that is statistically different from zero but indistinguishable from the coefficient on core earnings [$F = 0.43, p = 0.512$].

Panel B shows coefficients estimates from alternative specifications of the $AE-DYNAMIC$ that are based on income before extraordinary items and discontinued operations. We consider column (A) a direct estimate of our theoretical dynamic. We rewrite the mean calculated theoretical values of the dynamic coefficients $(\delta_n`)$ in Table 4 Panel B for expositional convenience and to further compare the dynamic estimated coefficients with their theoretical counterparts based on the VAR estimation. Core earnings and shifted negative core earnings indifferently forecast one year ahead abnormal earnings, while purified special items do not significantly load in the dynamic. In addition, the coefficients on book value and dividends are broadly consistent with their calculated values in the VAR. While this is not entirely surprising, given that $AE-DYNAMIC$ is the outcome of the sum of the first three rows in the VAR, it validates our restricted coefficients in the κ matrix which are mainly in the first three equations of the VAR and also ensures that the use of a different estimator for a truncated dependent variable is plausible. In column (B), we re-estimate the dynamic while replacing purified total special items (gains and losses) with purified *negative* special items calculated as the difference between reported *negative* special items and shifted negative core earnings (positive special items are set to equal zero here). Results are not sensitive to this specification. Finally, we estimate the dynamic using reported special items in column (C), in order to test the implications of ignoring to control for the core portion on special items. Results show that reported special items are statistically insignificant $(\delta_2 = 0.024, t = 1.56)$. When negative special items are used instead of special items gains and losses in column (D), the coefficient of reported *negative* special items increases slightly to 0.031, and is only significant at the 10% level.

Panel C results reveal that the earnings plug variables that allow the abnormal earnings dynamics to satisfy clean surplus are significant, but their coefficients are lower than reported and shifted core earnings. More importantly, the coefficient on sce_t is not affected by this alternative test, which rules out the possibility that the shifted negative core earnings result is an artifact of an omitted earnings variable from the dynamic.

Taken together, the results from Table 5 suggest that though reported special items have, *on average*, little forecasting ability for one year ahead abnormal earnings, they do include transitory and core partitions due to classification shifting. Our measure for sce_t appears to perform well in extracting the core component of special items and is equally statistically important as reported core earnings in forecasting one year ahead abnormal earnings. Failure to account for this core component of special items results in ignoring forecasting relevant information that is "hidden" within a reported transitory earnings category in the income statement.

[Insert Table 5 here]

5.4.2 Additional Tests for the Bad News Signaling Role of Shifted Negative Core Earnings in the Dynamic

Across all results in Table 5, the coefficient of shifted negative core earnings is slightly higher than the coefficient of core earnings. Building on our theoretical VAR, this is consistent with the possibility that sce_t provides a bad news signal for firms that mask their performance besides its fundamental forecasting role as an earnings variable. Nevertheless, the observed bad news effect is statistically insignificant in all tests in Table 5. One potential factor that might induce bias against finding a significant effect is constraining the coefficient on ce_t to be the same for positive and negative core earnings values and comparing it with the coefficient on sce_t that comprises only shifted negative core earnings. This is because positive and negative earnings have different properties (Jan and Ou 1995 and Collins et al. 1997), and negative earnings are found to be less informative about future earnings (Hayn 1995). We re-estimate the dynamic permitting the coefficient for negative core earnings to differ from those with positive values, in order to see if results change after controlling for the positive/negative partitions of core earnings. By the same token, we also allow the coefficient on purified special items to differ for negative values. Permitting the coefficient on purified special items to differ for negative observations relaxes the zero value constraint that we applied on positive special item in column

(B) of Table 5 Panel B, when $pute_t$ was measured as purified negative special items.[23]. The dynamic becomes:

$$ae_{t+1}^{ib} = \delta_1^{+/-} ce_t + \delta_1^{-} ce_t\_ind \times ce_t + \delta_2^{+/-} pute_t + \delta_2^{-} pute_t\_ind \times pute_t + \delta_3 sce_t + \delta_4 bv_t + \delta_5 dv + error_{t+1} \quad (16)$$

where ce_t_ind ($pute_t\_ind$) is an indicator variable that is equal to 1 if ce_t ($pute_t$) is negative and 0 otherwise. Hence, the bad news signaling test now depends on the statistical significance of $[\delta_3 - (\delta_1^{+/-} + \delta_1^{-})]$. The results in Table 6 show that although the coefficient of shifted negative core earnings ($\delta_3 = 0.519$) is higher than reported negative core earnings $[(\delta_1^{+/-} + \delta_1^{-}) = 0.407]$, the difference between the coefficients, which is the bad news signal, is still statistically insignificant $[F-value = 0.49, P-value = 0.482]$ similar to previous results. All purified special items coefficients are also insignificant (positive or negative) in the revised dynamic.

We conclude that the evidence of sce_t representing core expenses that the manager chooses to report as noncore expenses is convincing. The fundamental forecasting property of these expenses leads to their association with future profitability similar to core earnings. However, the possibility for sce_t to provide other relevant information beyond its earnings role, though theoretically appealing and consistent with the VAR estimation, seems to be over-optimistic.

[Insert Table 6 here]

[23] Compustat reports special items on a net basis. Since we focus on shifting expenses from core earnings to special items, sce_t will be zero for all positive special items observation in the dataset because it is estimated from negative special items. In column B of Table 5 Panel B, we run the analysis with only purified negative special items, restricting reported positive special items to be zero. Now, we consider permitting the coefficient on purified special items to differ for negative values which allows us to disentangle the adjusted negative special items (that are purified) from reported positive special items without throwing away positive special items or restricting them be equal to zero. Main results are not sensitive to these alternatives.

5.5 The Valuation Models Results

5.5.1 Main Results

Thus far, forecasting results support our measure of shifted negative core earnings, which is extracted from reported negative special items, and its ability to forecast future abnormal profitability. Since stock valuation is more complicated and reflects investors' *expectations* of future abnormal earnings rather than the actual abnormal earnings process, we now turn to testing whether stock prices act as if they fully reflect the information in the permanent component of negative special items about future abnormal earnings. Following Sougiannis (1994), we estimate the valuation models in the semi log form using the natural log of market values as the dependent variable to reduce the variance and skeweness of the residual[24].

Table 7 reports results on different tests of $CAE-MODEL$ and $CE-MODEL$ in Panels A and B, respectively. Similar to our forecasting tests, we re-write the implied theoretical coefficients from the VAR for sake of comparison. Untabulated Hausman test that is heteroscedastic and firm cluster-robust suggests that a fixed effects model is a better choice for analyzing the data over a random effects model. Though we report all coefficients in Table 7 using panel fixed effects models, untabulated random effects estimators show very consistent results.

In Panel A column (A), we estimate the valuation coefficients of the $CAE-MODEL$. Results reveal that the valuation coefficients of core abnormal earnings, book value and dividends are positive and statistically significant, and broadly consistent with their implied values from the VAR and the $AE-DYNAMIC$. The coefficient on core abnormal earnings is equal to 0.866. This is relatively close to its mean theoretical value of 0.529. The difference between the magnitudes is consistent with the evidence in Alfonso et al. (2015) that the market overvalues core earnings, when firms classification-shift. Book value has a coefficient equal to 0.317 which has the same sign but a smaller magnitude in relation to its theoretical value of 1.044. Dividends have a

[24] In untabulated results, we convert variables into their decile rankings and use the decile rankings in the valuation model rather than actual values. Results are not sensitive to this approach.

coefficient of 1.130 which has the same sign but a higher magnitude in relation to its theoretical counterpart of 0.561[25].

Both purified special items and shifted negative core earnings coefficients are substantially different from their implied theoretical values. The market attaches a positive and statistically significant coefficient of 0.653 to purified special items, in contrast to the predicted negative and small coefficient of −0.083. The coefficient on shifted negative core earnings of 0.568 is relatively similar in magnitude to purified special items, but is statistically insignificant, which is also inconsistent with its calculated theoretical value of 0.872 and its positive statistical significance in relation to prediction of future abnormal earnings previously reported. When we replace purified special items (gains and losses) with only purified negative special items in column (B), we obtain a smaller coefficient on shifted negative core earnings that is insignificant, and a higher statistically significant positive coefficient on purified negative special items. In column (C), we test the valuation model when the two components of special items are aggregated. Results show that the market attaches a statistically significant positive coefficient of 0.648 to reported special items, but that the difference between this coefficient and the coefficient of 0.866 on core abnormal earnings is statistically significant $[F-value=16.17, P-value=0.00]$.

In Panel B column (A), we estimate the valuation coefficients of the $CE-MODEL$. Similar to the $CAE-MODEL$, results indicate that the coefficients on core earnings, book value and dividends are qualitatively consistent with their theoretical values from the VAR estimation. The coefficient on core earnings is 0.922 and has a corresponding theoretical value of 0.592. The differential magnitudes between book value and dividends coefficients and their theoretical counterparts are similar to those in the $CAE-MODEL$. In contrast, the coefficient on purified special items has an opposite sign in relation to the calculated theoretical coefficient and the difference between the magnitude of the coefficient and its theoretical counterpart is obvious. Moreover, the coefficient on shifted negative core earnings of 0.595 is insignificantly different

[25] Hand and Landsman (2005) investigate different explanations for the pricing of dividends. In our models, we actually allow dividends to have forecasting and valuation effects, yet observe a higher valuation coefficient on dividends than its calculated theoretical value. Thought this is not the focus of our paper, we find it intuitively appealing from a theoretical perspective to link this excess in coefficient magnitude to corrections of the differences between the market estimation of the core abnormal earnings and book value coefficients that we observe here and their theoretical values.

from zero in comparison to the theoretical coefficient of 0.936 based on the VAR. We repeat the same tests in Panel B columns (B and C) as per Panel A columns (B and C) and the inferences we drew earlier do not change. Moreover, in untabulated results, we estimate the valuation models after adding ni_plug_t or ib_plug and all results are consistent.

[Insert Table 7 here]

5.5.2 Does the Market Anticipate the Incidence of Shifting?

So far, our valuation results suggest that the market acts as if it does not see through classification shifting. In addition, the market appears to overestimate the implications of special items on future abnormal earnings. One possible interpretation for the overvaluation of special items is that the market applies a higher coefficient on the entire amount of special items in order to mitigate its limited ability to identify the core element of special items. In this case, the market chooses to penalize suspected firms by placing an incremental valuation coefficient on their special items[26]. In order to test this, we estimate the following model:

$$MV_t = \lambda_0 + \lambda_1 ce_t + \lambda_2 te_t + \lambda_3 shift\_ind \times te_t + \lambda_4 bv_t + \lambda_5 dv_t \qquad (17)$$

where $shift\_ind$ is an indicator variable that is equal to one if $sce_t \neq 0$ and zero otherwise. If the market is able to identify the "incidence" of shifting, but cannot "quantify" the shifted component, we expect that the market attaches an incremental valuation coefficient to the special items interaction term and also values the shifters' special items similar to core earnings, that is $\lambda_3 > 0$ and $\lambda_1 = \lambda_2 + \lambda_3$. We estimate the valuation model using a fixed effect panel model and report the results in Table 8.

Table 8 reveals some interesting results. The coefficient on special items, $\lambda_2 = 0.491$, is significantly lower than core earnings, $\lambda_1 = 0.922$, $[F-value = 44.08, P-value = 0.00]$. The coefficient on the interaction term is significantly higher than zero, $\lambda_3 = 0.319 (t = 4.23)$, and

[26] Note that the majority of special items are expenses (negative data values), hence a positive coefficient on special items indicates their negative association with the market value. As in previous sections, results do not change when we use only negative special items.

both core earnings and shifters' special items coefficients are insignificantly different $[F - value = 3.91, P - value = 0.048]$.

Taken together, the valuation results suggest that stock prices do not fully impound the differing implications of special items components, because of the market limited ability to quantify the core and transitory elements of special items. Nevertheless, the market appears to be able to detect the incidence of shifting, rather than the magnitude of shifted earnings, and chooses to place a higher valuation coefficient on the entire amount of special items.

[Insert Table 8 here]

6. Conclusion

This paper examines core earnings misclassification from conceptual and empirical perspectives. It develops a robust forecasting and valuation framework that ties the evolution of a parsimonious set of accounting variables, which includes misclassified core earnings, to their valuation weights in the price models. The mapping of accounting variables into equity prices requires, besides a specific VAR characterization, only the clean surplus identity and the dividend discount model. The assumed VAR does not limit the generalizability of our empirical results, because we estimate our forecasting and valuation results from unrestricted regressions and compare the coefficients on the variables with their theoretical counterparts implied by our assumed underlying VAR. The conceptual analysis also serves as a solid basis for how one would expect misclassified core earnings to behave in forecasting and valuation. Specifically, it suggests two possible roles for negative core earnings that are opportunistically transferred to special items; an information role as a core earnings component and a bad news signaling role for lower future profitability.

We then develop an original metric of the misclassified operating expenses that is based on the McVay (2006) model. Our measure disentangles recurring expenses from nonrecurring real special items. It also accords with the plausible notion that not all firms with negative special items are misclassifying expenses, as is sensibly expected to be the case, and estimates the suspected shifted expenses at the firm-year level.

We test empirically the descriptive validity of our conceptual framework using different specifications of the models. Results validate our measure of shifted negative core earnings and show that our modeling procedures predict reasonable theoretical values for accounting variables coefficients. We provide evidence that shifted negative core earnings forecast one year ahead abnormal earnings in a similar fashion to reported core earnings. Although reported special items have limited forecasting ability in relation to one year ahead abnormal earnings; they include some "hidden" forecasting-relevant information due to classification shifting. The abnormal earnings dynamic results lend support to the ability of our classification shifting metric to extract this "core earnings" information content from special items. Purified special items do not significantly forecast future abnormal earnings, as broadly expected for transitory earnings. Although the theoretical bad news signal is indicated by the magnitude of the coefficient for shifted negative core earnings in abnormal earnings forecasts, the signal effect is only modest.

In relation to market valuation, we find that stock prices do not fully reflect the heterogeneity between the components of special items. Nevertheless, when we estimate the valuation model using reported special items and allow the coefficient on reported special items to vary by the occurrence of shifting, an interesting result emerges. We find that the market places an incremental significant coefficient on reported special items when shifting occurs. In addition, the market values the entire amount of special items similar to core earnings. We conclude that the market can, at best, detect the incidence of shifting, but has limited ability in measuring the respective amount of shifted earnings. Therefore, the market chooses to penalize shifters by valuing their special items, which are mostly losses, as if they are all shifted core earnings.

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APPENDIX

Variable Definitions

Variable	Measurement
ce_t	Core earnings = [Sales − Cost of Goods Sold − Selling, General and Administrative expenses (#13)] / Sale (#12)
Δce_{t+1}	Change in core earnings $= ce_{t+1} - ce_t$
ato_t	Assets turnover ratio= [sales (#12) $/\left(noa_t + noa_{t-1}\right)/2$, noa_i = operating assets − operating liabilities = [Total Assets (#6) − Cash (#1) and Short Term Investments (#32)] − [Total Assets (#6) − Total Debt (#9 + #34) − Book value of Common (#60) and Preferred Equity (#130) – Minority Interest (# 38)]. Average NOA is required to be positive.
Δato_t	Change in asset turnover ratio $= ato_t - ato_{t-1}$
acc_t	Operating accruals = [Net Income before Extraordinary Items (#123) − Cash from Operations (#308 − #124)] / Sales (#12) ;
Δsa_t	Percentage change in sales = [Sales_t (#12) $- \text{Sales}_{t-1}$] $/\text{Sales}_{t-1}$
$neg\Delta sa_t$	Percentage change in sales (Δsa_t) if (Δsa_t) is less than zero, and 0 otherwise.
$negsi_t$	Negative special items= [Special items (#17) / Sales (#12)] when special items are negative, and 0 otherwise.
MV_t	Market value three months after the fiscal year end = log (CRSP adjusted stock prices $\times$ number of outstanding shares)
bv_t	Book value of equity scaled by sales = Common equity(#60)/Sales (#12)
dv_t	Common dividends scaled by sales = Common dividends (#21) / Sales (#12)
te_t	Transitory earnings measured as special items (#17)/ Sales (#12) or as $negsi_t$ according to the model specification in the empirical test.

$pute_t$ Purified transitory earnings measured as purified special items or purified negative special items according to the model specification in the empirical test. The measurement approach is described in the text.

ae_t^{ni} Net income measure of abnormal earnings = [Net income (#172) – 0.12 × common equity (#60) at the beginning of the year] / Sales (#12)

ae_t^{ib} Income before extraordinary items and discontinued operations measure of abnormal earnings = [Income before extraordinary items (#18) / Sales (#12) – 0.12 × lagged common equity deflated by sales]

cae_t Core abnormal earnings = [Sales – Cost of Goods Sold – Selling, General and Administrative expenses] / Sales (#12) − 0.12 × lagged common equity deflated by sales]

sce_t Shifted negative core earnings measured as described in the text.

$shift\_ind_t \times sce_t$ Shifting indicator variable measured as 1 if $sce \neq 0$, and zero otherwise

Tables

Table 1

Models of Core Earnings Levels and Changes

Panel A: Core Earnings Level Model

$$ce_t = \eta_0 + \eta_1 ce_{t-1} + \eta_2 ato_t + \eta_3 acc_{t-1} + \eta_4 acc_t + \eta_5 \Delta sa_t + \eta_6 neg\Delta sa_t + error_t$$

Coeff.	Variable	Predicted sign	Mean coefficients		Median coefficients	
			Pooled OLS regression	Industry-year (Mean coeff.)	Pooled quintile regression	Industry-year (Median coeff.)
η_0	*Cons.*		0.034***	0.036	0.012***	0.036
			(18.25)		(35.98)	
η_1	ce_{t-1}	+	0.802***	0.802	0.908***	0.802
			(134.55)		(1718.66)	
η_2	ato_t	−	−0.001***	−0.001	−0.001***	−0.001
			(−4.85)		(−12.68)	
η_3	acc_{t-1}	−	−0.211***	−0.155	−0.153***	−0.145
			(−24.21)		(−184.20)	
η_4	acc_t	+	0.303***	0.223	0.122***	0.213
			(30.63)		(159.42)	
η_5	Δsa_t	+	0.112***	0.092	0.046***	0.072
			(24.37)		(71.28)	
η_6	$neg\Delta sa_t$	+	0.415***	0.384	0.209***	0.324
			(23.19)		(104.54)	
R^2			75.62%	79.56%		82.34%
Pseudo R^2					55.52%	

Panel B: Core Earnings Change Model

$$\Delta ce_t = \theta_0 + \theta_1 ce_{t-1} + \theta_2 \Delta ce_{t-1} + \theta_3 \Delta ato_t + \theta_4 acc_{t-1} + \theta_5 acc_t + \theta_6 \Delta sa_t + \theta_7 neg\Delta sa_t + error_t$$

Coeff.	Variable	Predicted sign	Mean coefficients		Median coefficients	
			Pooled OLS regression	Industry-year (Mean coeff.)	Pooled quintile regression	Industry-year (Median coeff.)
θ_0	*Cons.*		0.020***	0.024	0.012***	0.019
			(15.69)		(43.76)	
θ_1	ce_{t-1}	−	−0.139***	−0.153	−0.128***	−0.156
			(-25.65)		(−238.47)	
θ_2	Δce_{t-1}	−	−0.026***	−0.041	−0.0166***	−0.028
			(−3.04)		(−18.89)	
θ_3	Δato_t	+	0.006***	0.005	0.002***	0.004
			(12.45)		(21.47)	
θ_4	acc_{t-1}	−	−0.170***	−0.134	−0.177***	−0.130
			(−24.62)		(−206.11)	
θ_5	acc_t	+	0.226***	0.188	0.112***	0.194
			(31.70)		(143.64)	
θ_6	Δsa_t	+	0.113***	0.087	0.054***	0.063
			(32.25)		(81.18)	
θ_7	$neg\Delta sa_t$	+	0.367***	0.321	0.217***	0.320
			(26.21)		(105.12)	
R^2			35.03%	51.83%		52.47%
Pseudo R^2					11.93%	

The table provides fit statistics of the core earnings level and changes models. Standard errors are robust standard errors. *,**and*** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix.

Table 2

Regressions of Unexpected Core Earnings and Future Unexpected Change in Core Earnings on Negative Special Items

Panel A: Unexpected Core Earnings Model $unce_t = \omega_0 + \omega_1 negsi_t + error_t$

Dependent Variable: $unce_t = [ce_{i,t} - E(ce_{i,t})]$

Coefficient	Variables	Predicted sign	OLS Pooled estimator
ω_0	*Cons.*	?	−0.001*
ω_1	$negsi_t$	(+)	0.042***
R^2			0.04%

Panel B: Unexpected Change in Core Earnings Model $un\Delta ce_{t+1} = \phi_0 + \phi_1 negsi_t + error_{t+1}$

Dependent Variable: $un\Delta ce_t = [\Delta ce_{t+1} - E(\Delta ce_{t+1})]$

Coefficient	Variables	Predicted sign	OLS pooled Estimator
ϕ_0	*Cons.*	?	0.002***
ϕ_1	$negsi_t$	(−)	−0.035***
R^2			0.03%

The table provides results of pooled OLS regressions of current unexpected core earnings on current negative special items, and future unexpected core earnings change on current negative special items. Standard errors are clustered by firm and year. *,**and*** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively. Negative special items $negsi_t$, are measured in absolute terms. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix.

Table 3

Descriptive Statistics

Panel A: Distributional Statistics

Variable	Mean	SD	Min	Max
Market value (in $ million)	1933.052	11546.29	0.158	507216.7
Net income measure of Abnormal earnings	−0.156	0.484	−3.494	0.282
Income before extraordinary items measure of Abnormal earnings	−0.154	0.473	−3.318	0.248
Abnormal core earnings	−0.004	0.363	−2.429	0.547
Core earnings	0.082	0.353	−2.321	0.735
Reported negative special items	−0.027	0.091	−0.697	0
Shifted negative core earnings	−0.002	0.009	−0.071	0
Nonzero shifted core expenses	−0.011	0.018	−0.071	−6.190
True special items	−0.021	0.089	−0.697	0.152
Book value	0.805	1.039	−0.393	7.078
Dividends	0.015	0.042	0	0.312

Panel B: Correlation Matrix (Pearson Top; Spearman Bottom) with Respective *p*-values in Parentheses

Variable	Core earnings	Purified special items	Shifted negative core earnings	Book value	Dividends
Core earnings		0.100	0.075	0.303	0.399
Purified special items	0.245		0.584	0.015	0.093
Shifted negative core earnings	0.143	0.501		−0.020	0.071
Book value	− 0.259	−0.108	−0.078		0.101
Dividends	0.248	0.047	0.026	0.257	

The table provides descriptive statistics for main variables in the analysis. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix.

Table 4

Estimated Coefficients of the Vector Autoregression (VAR) and Implied Theoretical Forecasting and Valuation Coefficients

Panel A: The VAR Estimated κ Matrix

The VAR:

$$z_{t+1}\begin{bmatrix} cae_{t+1} \\ pute_{t+1} \\ sce_{t+1} \\ bv_{t+1} \\ dv_{t+1} \end{bmatrix} = \kappa \begin{bmatrix} \kappa_{11} & 0 & \kappa_{13} & \kappa_{14} & \kappa_{15} \\ 0 & \kappa_{22} & 0 & 0 & 0 \\ 0 & 0 & \kappa_{33} & 0 & 0 \\ \kappa_{41} & \kappa_{42} & \kappa_{43} & \kappa_{44} & \kappa_{45} \\ \kappa_{51} & \kappa_{52} & \kappa_{53} & \kappa_{54} & \kappa_{55} \end{bmatrix} \times z_t \begin{bmatrix} cae_t \\ pute_t \\ sce_t \\ bv_t \\ dv_t \end{bmatrix} + u_{t+1} \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \\ \varepsilon_{3t+1} \\ \varepsilon_{4t+1} \\ \varepsilon_{5t+1} \end{bmatrix}$$

Dependent variable	**Explanatory variables**				
	cae_t	$pute_t$	sce_t	bv_t	dv_t
cae_{t+1}	0.316*** (61.43)	0	0.225** (2.10)	−0.145*** (−75.24)	0.312*** (7.19)
$pute_{t+1}$	0	− 0.044*** (−8.37)	0	0	0
sce_{t+1}	0	0	0.166*** (10.39)	0	0
bv_{t+1}	0.205*** (14.16)	0.085** (2.16)	−0.639* (−1.91)	0.539*** (100.27)	0.145 (1.20)
	0	0	0	0.527*** (119.64)	0
dv_{t+1}	0.061*** (33.82)	0.047*** (8.24)	0.194*** (4.29)	0.004*** (9.77)	0.987*** (154.64)

Panel B: Calculated Abnormal Earnings Dynamic and Market Valuation Parameters Based on the VAR Estimated κ Matrix

The Forecasting Model: $ae_{t+1} = \delta_1 ce_t + \delta_2 pute_t + \delta_3 sce_t + \delta_4 bv_t + \delta_5 dv_t + \zeta_{t+1}$

Coefficient	Theoretical value based on κ matrix	Calculated value
δ_1`	$\kappa_{11}R$	0.354
δ_2`	$\kappa_{22} - \kappa_{11} + \kappa_{11}R$	−0.006
δ_3`	$\kappa_{13} + \kappa_{33} - \kappa_{11} + \kappa_{11}R$	0.429
δ_4`	$\kappa_{14} + \kappa_{11} - \kappa_{11}R$	− 0.183
δ_5`	$\kappa_{15} + \kappa_{11} - \kappa_{11}R$	0.274
δ_3`−$\delta_1$`	$\kappa_{13} + \kappa_{33} - \kappa_{11}$	0.075

Table 4 (continued)

Core Abnormal Earnings Valuation Model $(CAE-MODEL)$:

$$MV_t = \beta_1 cae_t + \beta_2 pute_t + \beta_3 sce_t + \beta_4 bv_t + \beta_5 dv_t$$

Coeff.	Theoretical value based on κ matrix	Calculated value based on estimated κ matrix I	II	III	Mean
β_1`	$\frac{\kappa_{11}(R-\kappa_{44})+\kappa_{14}\kappa_{41}}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.457	0.488	0.642	0.529
β_2`	$\frac{\kappa_{22}(R-\kappa_{11})(R-\kappa_{44})+\kappa_{14}(R\kappa_{42}-\kappa_{22}\kappa_{41})}{[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})](R-\kappa_{22})}$	−0.091	−0.097	−0.062	−0.083
β_3`	$\frac{[\kappa_{33}(R-\kappa_{11})+R\kappa_{13}](R-\kappa_{44})+\kappa_{14}(R\kappa_{43}-\kappa_{33}\kappa_{41})}{[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})](R-\kappa_{33})}$	1.036	0.760	0.821	0.872
β_4`	$\frac{(R-\kappa_{11})(R-\kappa_{44})+\kappa_{14}(R-\kappa_{41})}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.993	1.060	1.078	1.044
β_5`	$\frac{\kappa_{15}(R-\kappa_{44})+\kappa_{14}\kappa_{45}}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.476	0.574	0.634	0.561
β_3`$-\beta_1$`	$\frac{R[(\kappa_{13}+\kappa_{33}-\kappa_{11})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}-\kappa_{43})]}{(R-\kappa_{33})[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})]}$	0.579	0.273	0.179	0.344

Table 4 (continued)

Core Earnings Valuation Model $(\boldsymbol{CE-MODEL})$ **:** $MV_t = \beta_1^* ce_t + \beta_2^* pute_t + \beta_3^* sce_t + \beta_4^* bv_t + \beta_5^* dv_t$

Coeff.	Theoretical value based on κ matrix	Calculated value based on estimated κ matrix I	II	III	Mean
$\beta_1^{*`}$	$\frac{R[\kappa_{11}(R-\kappa_{44})+\kappa_{14}\kappa_{41}]}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.512	0.546	0.719	0.592
$\beta_2^{*`}$	$\frac{R\left[\kappa_{14}(\kappa_{42}+\kappa_{41}(R-\kappa_{22}-1))+(R-\kappa_{44})(\kappa_{22}+\kappa_{11}(R-\kappa_{22}-1))\right]}{\left[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})\right](R-\kappa_{22})}$	−0.036	−0.039	0.015	−0.02
$\beta_3^{*`}$	$\frac{R\left[\kappa_{14}(\kappa_{43}+\kappa_{41}(R-\kappa_{33}-1))+(R-\kappa_{44})(\kappa_{13}+\kappa_{33}+\kappa_{11}(R-\kappa_{33}-1))\right]}{\left[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})\right](R-\kappa_{33})}$	1.091	0.818	0.898	0.936
$\beta_4^{*`}$	$\frac{R\left[\kappa_{14}-\kappa_{14}\kappa_{41}-(\kappa_{11}-1)(R-\kappa_{44})\right]}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.939	1.001	1.000	0.98
$\beta_5^{*`}$	$\frac{\kappa_{14}(\kappa_{41}+\kappa_{45}-\kappa_{41}R)+(R-\kappa_{44})(\kappa_{11}+\kappa_{15}-\kappa_{11}R)}{(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})}$	0.421	0.516	0.557	0.498
$\beta_3^{*`}-\beta_1^{*`}$	$\frac{R\left[(\kappa_{13}+\kappa_{33}-\kappa_{11})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}-\kappa_{43})\right]}{(R-\kappa_{33})\left[(R-\kappa_{11}-\kappa_{15})(R-\kappa_{44})-\kappa_{14}(\kappa_{41}+\kappa_{45})\right]}$	0.579	0.273	0.179	0.344

The table provides results of the VAR estimated κ matrix and theoretical counterparts of the abnormal earnings dynamics and valuation models coefficients. The VAR equations are estimated using fixed effects panel data models, except for the truncated dependent variables equations (shifted core earnings and dividends) where censored regressions with fixed effects are used. All VAR equations are estimated with intercepts and suppressed here. *,** ,***indicate significance at the 0.1, 0.05 and the 0.01 levels, respectively. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix.
(I) Significant and insignificant estimated κ, (II) Only significant (at least at the 5% level) estimated κ, (III) Further restrictions on the book value dynamic $\kappa_{41}=0$, $\kappa_{42}=0$, $\kappa_{43}=0$, $\kappa_{45}=0$, and (Mean) the mean of the theoretical value of the coefficient based on (I), (II), and (III).

Table 5

Coefficient Estimates of the Abnormal Earnings Dynamic- *AE – DYNAMIC*

Panel A: The Abnormal Earnings Dynamic Using a Net Income Measure of Abnormal Earnings

$$ae_{t+1} = \delta_0 + \delta_1 ce_t + \delta_2 pute_t + \delta_3 sce_t + \delta_4 b_t + \delta_5 d_t + error_{t+1}$$

Dependent Variable : ae^{ni}_{t+1}

		Estimators			
Coefficient	**Variable**	**Pooled OLS**	**Fama-Macbeth**	**Random Effects**	**Fixed Effects**
δ_0	*Cons.*	− 0.052*** (− 17.60)	−0.050*** (−7.85)	− 0.064*** (−17.57)	− 0.014**** (−5.11)
δ_1	ce_t	0.727*** (57.06)	0.709*** (28.21)	0.573*** (96.50)	0.409*** (56.11)
δ_2	$pute_t$	0.274*** (6.63)	0.269*** (5.58)	0.082*** (4.44)	0.011 (0.61)
δ_3	sce_t	1.218*** (3.52)	1.211*** (2.89)	0.670*** (4.13)	0.519*** (3.11)
δ_4	bv_t	− 0.193*** (− 57.95)	−0.191*** (−30.10)	− 0.202*** (− 100.38)	− 0.209*** (−83.79)
δ_5 (Bad News)	dv_t	0.354*** (6.07)	0.391*** (6.35)	0.447*** (9.22)	0.195*** (3.25)
Shifting Signal $\delta_3 - \delta_1$		0.491	0.502	0.097	0.11
Wald Test: $F - Value$ $(P - Value)$		2.01 0.1566	1.43 0.2458	0.34 0.5584	0.43 0.5123
Hausman-χ^2 (p – value)					1966.02 (0.00)
Heteroscedastic-and firm cluster-robust Hausman-*Sargan - Hansen statistic* (p – value)					324.195 (0.00)
Adjusted R^2		0.60	0.60	0.60	0.60

Panel B: The Abnormal Earnings Dynamic Using an Income before Extraordinary Items Measure of Abnormal Earnings

$$ae^{ib}_{t+1} = \delta_0 + \delta_1 ce_t + \delta_2 pute_t + \delta_3 cse_t + \delta_4 bv_t + \delta_5 dv_t + error_{t+1}$$

Dependent Variable : ae^{ib}_{t+1}

		Fixed effects estimators				
Coefficient	**Variable**	**(A)** With purified special items & shifted core earnings		**(B)** With purified negative special items & shifted core earnings	**(C)** With only reported special items	**(D)** With only reported negative special items
		δ_n	δ_n`			
δ_0	*Cons.*	−0.015*** (−5.89)		−0.015*** (−5.82)	−0.016*** (−6.11)	−0.015*** (−5.97)
δ_1	ce_t	0.398*** (57.26)	0.354	0.398*** (57.06)	0.398*** (57.24)	0.397*** (57.02)
δ_2	$pute_t$	−0.007 (−0.38)	−0.006	−0.001 (−0.05)		
	te_t				0.024 (1.56)	0.0305* (1.88)
δ_3	sce_t	0.526*** (3.30)	0.429	0.501*** (3.14)		
δ_4	bv_t	−0.203*** (−85.57)	− 0.183	−0.203*** (−85.60)	−0.203*** (−85.52)	−0.203*** (−85.55)
δ_5	dv_t	0.177*** (3.11)	0.274	0.117*** (3.11)	0.175*** (3.07)	0.176*** (3.08)
(Bad News) Shifting Signal $\delta_3 - \delta_1$		0.129	0.075			
Wald Test: $F - Value$ ($P - Value$)		0.64 0.4237				
Adjusted R^2		0.57		0.57	0.57	0.57

Panel C: Abnormal Earnings Dynamic with the Earnings "plug" Variables:

$$ae_{t+1} = \delta_0 + \delta_1 ce_t + \delta_2 pute_t + \delta_3 cse_t + \delta_4 bv_t + \delta_5 dv_t + \delta_6 plug + error_{t+1}$$

		Fixed effects estimators	
		Abnormal earnings dependent variable	
Coefficient	**Variable**	**Income before extraordinary items and discontinued operations** ae^{ni}_{t+1}	**Net income** ae^{ib}_{t+1}
δ_0	*Cons.*	0.005	0.015***
		(1.42)	(4.79)
δ_1	ce_t	0.407***	0.396***
		(55.93)	(57.13)
δ_2	$pute_t$	0.012	−0.004
		(0.55)	(−0.24)
δ_3	sce_t	0.522***	0.520***
		(3.13)	(3.28)
δ_4	bv_t	−0.210***	−0.205***
		(−84.38)	(−86.52)
δ_5	dv_t	0.190***	0.174***
		(3.18)	(3.07)
δ_6	$plug$	0.155***	0.267***
		(10.61)	(15.88)
Adjusted R^2		0.57	0.58

The table provides results of the abnormal earnings dynamics estimated coefficients.*,** ,***indicates significance at the 0.1, 0.05 and the 0.01 levels, respectively. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix.

Panel A; reports coefficient estimates for the $AE - DYNAMIC$ using OLS, Fama-McBeth regressions, panel random effects, and panel fixed effects models. Abnormal earnings are measured using net income. *t*-statistics for the Fama-Macbeth regressions are Newey-West adjusted with a lag of 2. Results don't change using different lags

Panel B; reports coefficient estimates for different specifications of the $AE - DYNAMIC$ using a panel fixed effects model. Abnormal earnings are measured using income before extraordinary items and discontinued operations.

Panel C: reports coefficient estimates after including the earnings plug variable as an additional explanatory variable in the dynamics.

Table 6

Coefficient Estimates of the Abnormal Earnings Dynamic with Positive/Negative Earnings Partitions

Abnormal Earnings Dynamic with Positive/Negative Earnings Variables:

$$ae_{t+1}^{ib} = \delta_0 + \delta_1^{+/-} ce_t + \delta_1^{-} ce_t\_ind \times ce_t + \delta_2^{+/-} pute_t + \delta_2^{-} pute_t\_ind \times pute_t + \delta_3 sce_t + \delta_4 bv_t + \delta_5 dv + error_{t+1}$$

Coefficient	**Variable**	**Fixed effects estimator**
δ_0	$Cons.$	−0.010***
		(−2.92)
$\delta_1^{+/-}$	ce_t	0.366***
		(20.06)
δ_1^{-}	$ce_t\_ind \times ce_t$	0.041*
		(1.88)
$\delta_2^{+/-}$	$pute_t$	−0.100
		(−1.39)
δ_2^{-}	$pute_t\_ind \times pute_t$	0.101
		(1.33)
δ_3	sce_t	0.519***
		(3.24)
δ_4	bv_t	−0.202***
		(−83.59)
δ_5	dv_t	0.188***
		(3.29)
(Bad News)		
Shifting Signal		
$[\delta_3 - (\delta_1^{+/-} + \delta_1^{-})]$		0.112
Wald Test:		
$F-Value$		0.49
$(P-Value)$		(0.4819)
Adjusted R^2		0.57

The table provides results of the abnormal earnings dynamics estimated with positive/negative earnings variables. ce_t_ind is an indicator variable that is equal to 1 if ce_t is negative, and 0 otherwise. $pute_t\_ind$ is an indicator variable that is equal to 1 if $pute_t$ is negative, and 0 otherwise. Abnormal earnings are measured using income before extraordinary items and discontinued operations. *,** ,***indicates significance at the 0.1, 0.05 and the 0.01 levels, respectively. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix

Table 7

Coefficient Estimates of the Valuation Models

Panel A: Core Abnormal Earnings Valuation Model $(CAE-MODEL)$

$$MV_t = \beta_1 cae_t + \beta_2 pute_t + \beta_3 sce_t + \beta_4 bv_t + \beta_5 dv_t$$

		Fixed effects estimators			
Coefficient	**Variable**	**(A)** With purified special items & shifted core expenses		**(B)** With purified negative special items & shifted core expenses	**(C)** With only reported special items
		β_n	β_n`		
β_0	*Cons.*	4.994***		4.999***	4.994***
		(699.79)		(697.73)	(701.39)
β_1	cae_t	0.866***	0.529	0.856***	0.866***
		(43.84)		(43.21)	(43.84)
β_2	$pute_t$	0.653***	−0.083	0.784***	
		(12.10)		(13.72)	
	te_t				0.648***
					(14.20)
β_3	sce_t	0.568	0.872	0.176	
		(1.20)		(0.37)	
β_4	bv_t	0.317***	1.044	0.317***	0.317***
		(42.51)		(42.58)	(42.52)
β_5	dv_t	1.130***	0.561	1.137***	1.131***
		(6.58)		(6.63)	(6.59)
Adjusted R^2		0.09		0.09	0.09

Panel B: Core Earnings Valuation Model $(CE-MODEL)$

$$MV_t = \beta_1 ce_t + \beta_2 pute_t + \beta_3 sce_t + \beta_4 bv_t + \beta_5 dv_t$$

Coefficient	Variable	Fixed effects estimators (A) With true special items & shifted core expenses		(B) With true negative special items & shifted core expenses	(C) With only reported special items
		β_n^*	$\beta_n^{*`}$		
β_0^*	*Cons.*	4.869*** (701.36)		4.874*** (698.66)	4.869*** (702.93)
β_1^*	ce_t	0.922*** (50.84)	0.592	0.912*** (50.12)	0.922*** (50.84)
β_2^*	$pute_t$	0.681*** (13.94)	−0.02	0.796*** (15.40)	
	te_t				0.676*** (16.41)
β_3^*	sce_t	0.595 (1.36)	0.936	0.261 (0.59)	
β_4^*	bv_t	0.272*** (42.48)	0.98	0.272*** (42.60)	0.272*** (42.48)
β_5^*	dv_t	0.995*** (6.29)	0.498	0.999*** (6.32)	0.995*** (6.29)
Adjusted R^2		0.08		0.08	0.08

The table provides results of the valuation models. All implied theoretical counterparts of valuation coefficients are based on mean theoretical values reported in Table 4 (Mean). *** indicates significance at 0.01 level. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix

Table 8

The Valuation Models and the Incidence of Shifting

The $CE-MODEL$ with a Shifting Indicator

$MV_t = \lambda_0 + \lambda_1 ce_t + \lambda_2 te_t + \lambda_3 shift\_ind \times te_t + \lambda_4 bv_t + \lambda_5 dv_t$

Coefficient	Variable	Fixed effects estimators Valuation Models
λ_0	$Cons.$	4.870***
		(702.75)
λ_1	ce_t	0.922***
		(50.87)
λ_2	te_t	0.491***
		(8.15)
λ_3	$shift\_ind_t \times te_t$	0.319***
		(4.23)
λ_4	bv_t	0.271***
		(42.39)
λ_5	dv_t	1.002***
		(6.34)
Wald Test:		
$\lambda_1 = \lambda_2 + \lambda_3$		
$F-Value$		3.91
$(P-Value)$		0.048
Adjusted R^2		0.08

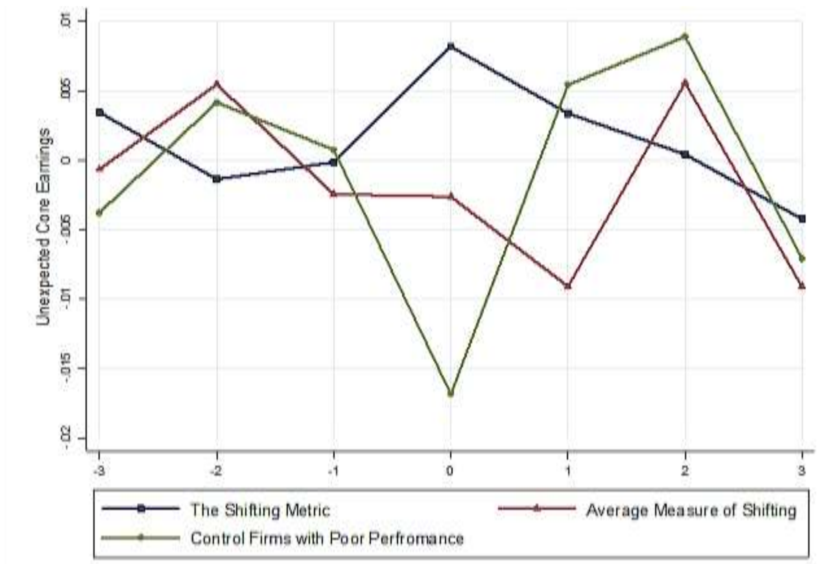
The table provides results of the valuation model estimated with a shifting indicator variable that interacts with reported special items. *,** ,***indicates significance at the 0.1, 0.05 and the 0.01 levels, respectively. Variables are winsorized at the 1st and 99th percentiles. All variables are defined in the appendix

Figures

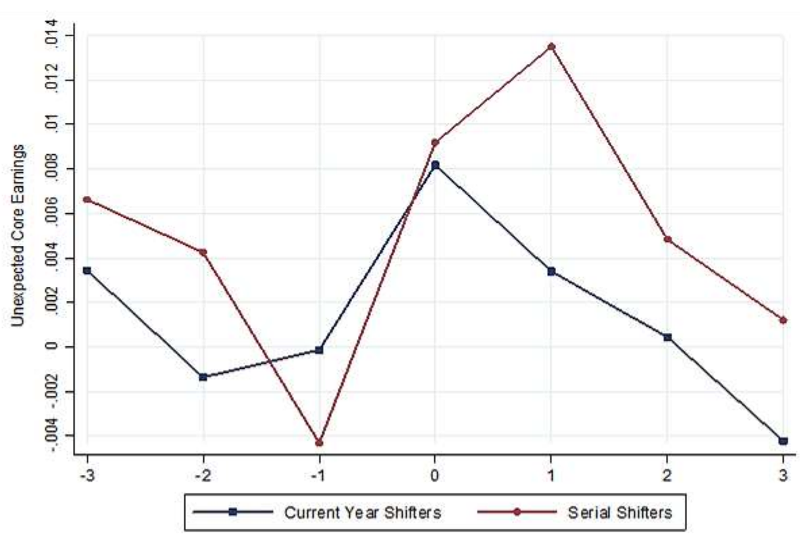
Figure 1

Inter-Temporal Analysis of Unexpected Core Earnings

Panel A: A Seven-Year Window Analysis of Unexpected Core Earnings Surrounding the Shifting Metric, an Average Measure of Shifting and a Control Firms' Industry Measure of Shifting



Panel B: A Seven-Year Window Analysis of Unexpected Core Earnings Surrounding the Shifting Metric for Current Shifters and Serial Shifters

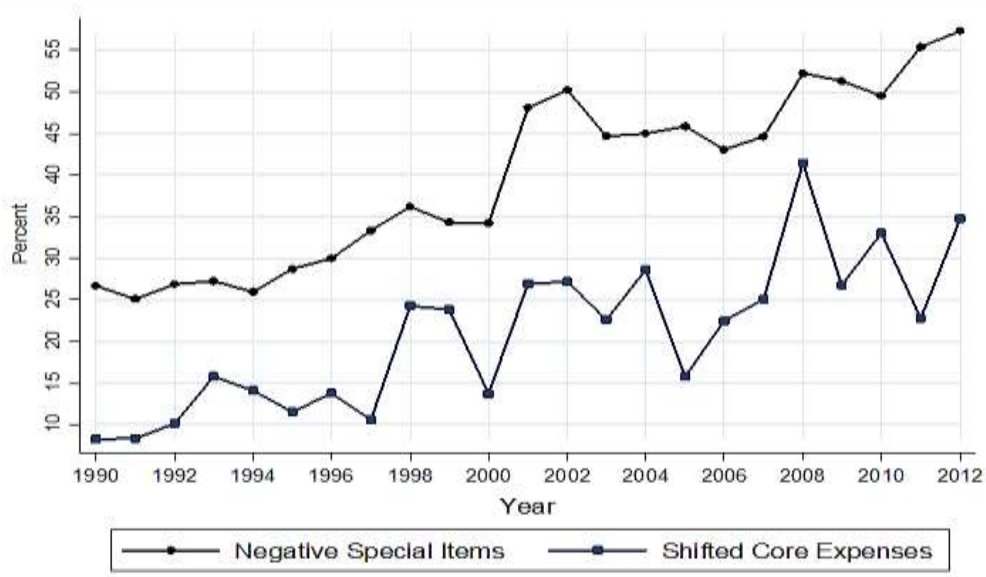


The figure presents the time series properties of unexpected core earnings surrounding the negative special items reporting for purposes of shifting or as a result of poor performance. Year 0 is the event year where the shifting/poor performance measure has a non-zero value.

Figure 2

Annual Trend of the Frequency of Negative Special Items and Shifted Negative Core Earnings

Panel A: Percentage of Firms Reporting Negative Special Items and Shifting Negative Core Earnings



Panel B: Percentage of Negative Special items Firms that Shifted Negative Core Earnings

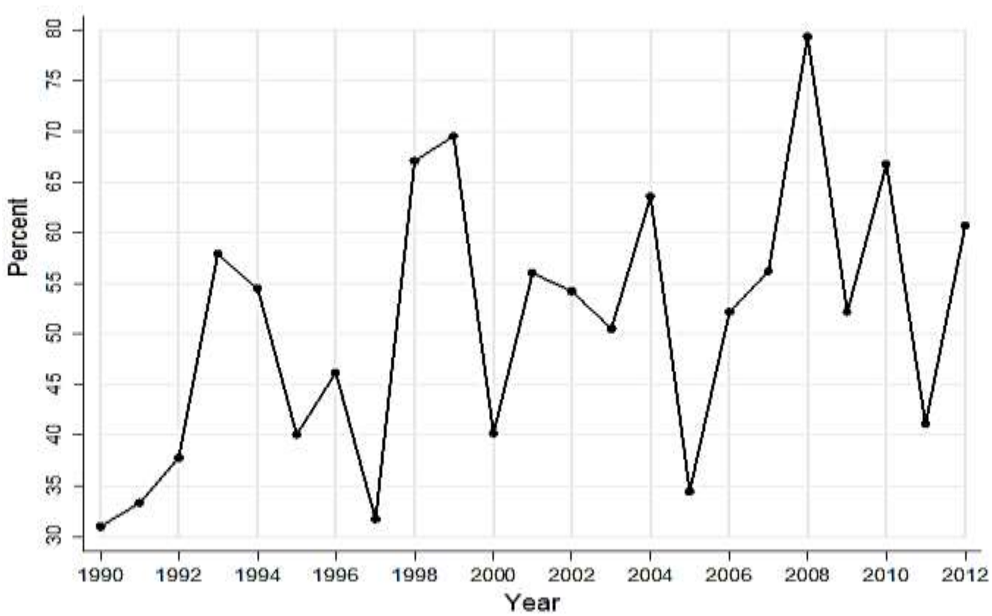
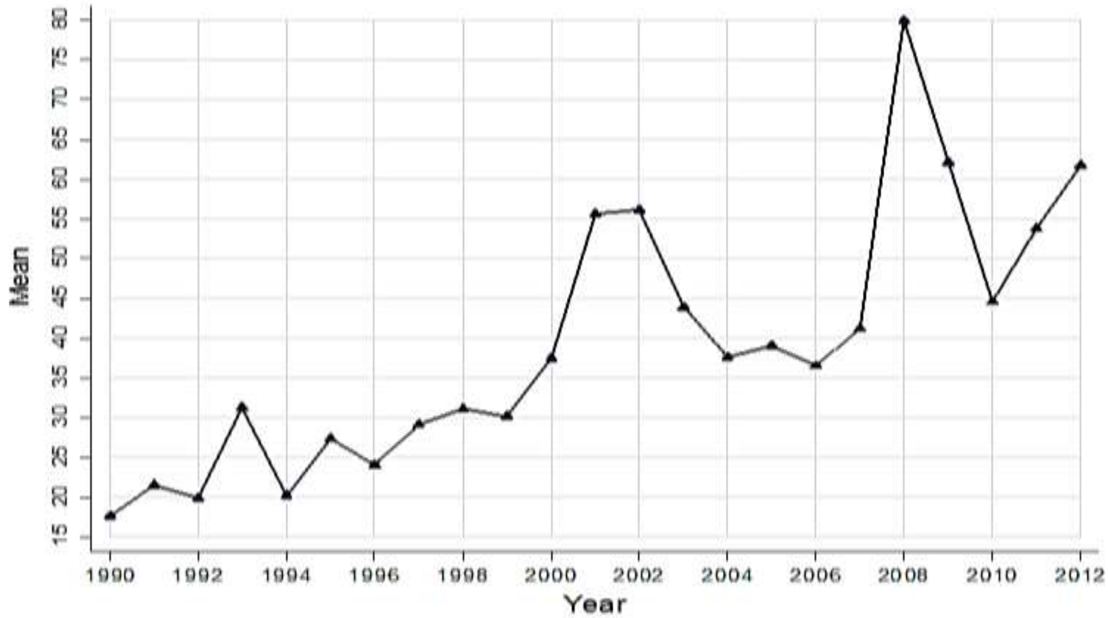


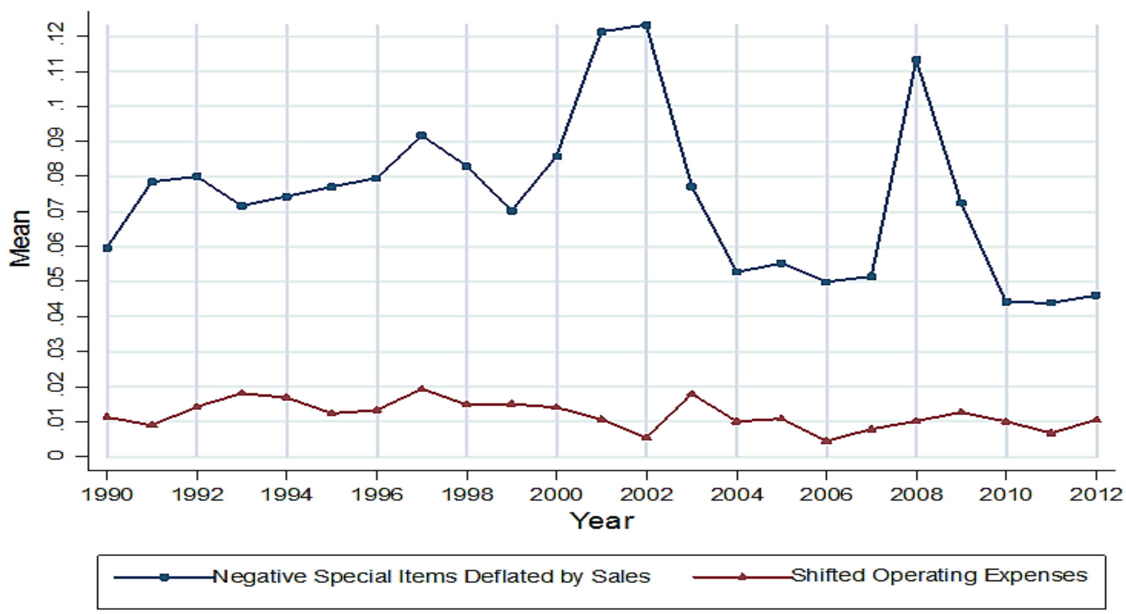
Figure 3

Annual Trend of the Magnitude of Negative Special Items and Shifted Negative Core Earnings

Panel A: Mean of the Absolute Value of Negative Special Items Reported by Negative Special Items Firms



Panel B: Mean of the Absolute Values of Negative Special Items Deflated by Sales and Shifted Negative Core Earnings



Chapter 4: On Negative Core Earnings Misclassification

1. Introduction

Standard textbooks on financial statement analysis suggest excluding special items when forecasting future earnings. This is because special items have significantly lower information content than core earnings. Recent research documents a substantial increase in the magnitude and persistence of negative special items, which is not fully explained by corresponding changes in the business environment that could have resulted in recognizing shocks outside core earnings. This paper provides evidence on how the manager's misclassification of negative core earnings (operating expenses and losses) as negative special items (McVay 2006) affects special items reporting and the market valuation of special items. We develop a simple framework that demonstrates a scenario when the manager is more likely to misclassify earnings. The analysis considers the flexibility allowed under GAAP in presenting earnings-line items and highlights the case when the earnings presentation is discretionary (within-GAAP) versus manipulative (non-GAAP). In the current setting, investors are not able to perfectly observe the negative core earnings misclassification, and depend on reporting signals in the income statements to infer it. When the signal of misclassification is of low quality, investors' expectations of future profitability conditional on the signal contain noise that enters stock prices, which in turn temporarily diverge from the intrinsic values.

We then develop empirical proxies for the main theoretical constructs to capture the negative core earnings misclassification phenomenon. The empirical results contribute to our understanding of prior empirical results on negative special items and expand current research in many aspects. First, We provide evidence that the propensity of the firm to report the highest (lowest) negative special items' magnitude in the market increases (decreases) with the difference between last year's reported core earnings and current year's expected core earnings. Using logistic regressions, We find that this core earnings difference is a main determinant of the decision of reporting large negative special items, after controlling for factors associated with negative special items recognition. This result expands the evidence in McVay (2006) that negative special items are used to hide negative core earnings, by showing *ex ante* when this is more likely to take place. We then examine the extent to which large negative special items reporting is attributable to either discretion allowed under GAAP or violation of GAAP. Interestingly, the evidence suggests that extremely large negative special items represent GAAP violation rather than allowable management discretion. Therefore, in addition to the economic activity explanation for the increase in special items reporting as suggested by Donelson et al. (2011), our results suggest that the manager's motive to manage core earnings is a primary determinant of the magnitude of negative special items.

Second, moving to the fundamental composition of negative special items, we split negative special items into two additive components; one that reflects misclassified negative core earnings (accounting misclassification) and another representing real negative special items (economic conditions). Using logistic regressions, we provide evidence that the association between negative special items and subsequent restatements is mainly attributable to misclassified negative core earnings rather than real special items at the time of misstatement, after controlling for other factors associated with future restatements. These results improve the results in Cain et al. (2014) who use a different approach to split negative special items into low and high quality special items components, but provide results of significant associations of both components and future restatements.

Third, we provide strong evidence that the ability of negative special items to forecast lower future abnormal earnings, earnings, and earnings before special items is mostly attributable to the misclassification of negative core earnings. This expands the results in Fairfield et al. (2009), Burgstahler et al. (2002) and Cready et al. (2010), by showing that while negative special items have significant but low implications for future profitability, they contain a core component that forecasts future profitability for a period up to three years, similar to reported core earnings in the income statement. These findings are important because while some standard textbooks on financial statement analysis suggest excluding special items when forecasting future profit margin (Easton et al. 2008, Lundholm and Sloan 2004), the present paper shows that this might be "less harmful" if applied only on *adjusted* negative special items that represent unusual events. Quantifying the core composition of negative special items provides one way for such an adjustment.

Fourth, we provide evidence that stock prices reflect the lower persistence of negative special items in comparison to core earnings, but appear not to fully impound the heterogeneous implications of special items components for future earnings. Further test results suggest that investors are not able to track the movement of negative core earnings to negative special items and rely on reporting signals in the income statement to infer this movement. The results reveal that the investors' perceived signal is noisy and induces errors in stock prices, such that the stock return association with negative special items changes with the degree of the reporting signal, but this change does not correspond with any improvement in negative special items predictability for future earnings. In contrast, an informative signal of misclassification that is associated with a steady improvement in negative special items predictability is not accompanied by a consistent price adjustment.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 is a description of the data. Section 4 presents results of the manager's misclassification decision. Section 5 describes the negative special items decomposition approach and reports results on the validation of the approach. Section 6 reports the forecasting and pricing results of negative special items components. In section 7, we present the misclassification signal tests and results. The final section is a summary of the main findings of this paper.

2. Theoretical Motivation and Modeling

The model setup assumes an accounting system that processes transactions and produces the base information for financial statements that is subsequently mapped into an earnings report issued by the manager. We distinguish between a core earnings signal, c_t, which denotes a summary of the annual base information that is unbiased about the terminal value, and reported core earnings, rc_t, which map the current core earnings signal.

Near to the end of year t, if the manager privately observes that c_t is lower than a certain threshold, such as last year's reported core earnings, he can shift some negative core earnings to current period's special items to give a better picture for the firm's core profitability, and then reports earnings that are biased with respect to the underlying core earnings signal in the following manner:

$$rc_t = c_t + \lambda_t \tag{1}$$

where λ_t denotes the level of misclassification. Although λ_t inflates rc_t relative to c_t, the increase in rc_t is offset by a decrease (an increase) in current period's (negative) special items and hence bottom line earnings are not affected. Nevertheless, λ_t is likely to affect investors' perceptions because different line items receive different weights from investors when setting stock prices.

Assume the following function for λ_t:

$$\lambda_t = f_j\left(\rho\, G_t, I_t, \zeta_t\right) \tag{2}$$

where G_t denotes current accounting standards (GAAP), I_t is the manager's private information about the firm's core earnings signal and ζ_t is a random shock. ρ is a reporting parameter that captures the degree to which λ_t is a transformation of G_t. $\rho = (0,1]$ is the acceptable range where the manager's movement of expenses is discretionary, within GAAP and less likely to raise red flags for outside monitors. ρ is limited not to equal zero, because G_t acts as background information for the manager's classification choice. If ρ is equal to unity, λ_t is perfect transformation of GAAP. However, if $\rho < 0$, λ_t represents GAAP violation rather than allowable management discretion.

Though λ_t is not communicated to investors by the manager, there is a probability that investors make some inferences about the misclassification of earnings conditional on potential misclassification signals in reported statements, sig_t. This implies that:

$$sig_t \stackrel{\text{def}}{=} \lambda_t + \xi_t \tag{3}$$

where ξ_t is a disturbance term (garbling in the misclassification signal received by investors). sig_t becomes noisy with higher first and second moments of the disturbance term (i.e. when $\mu_\xi \neq 0$ and $\sigma_\xi^2 > 0$).

Assuming rational expectations hypothesis (Mishkin1983 and Sheffrin 1996), the market assessment of future earnings conditional on sig_t is said to be rational when this assessment agrees with the actual earnings process at least in terms of the first moment:

$$E_t^m\left[e_{t+1} \mid sig_t\right] = E\left[e_{t+1} \mid \lambda_t\right] \mapsto P_t = V_t \tag{4}$$

where $E_t^m\left[.\right]$ is the market conditional expectations operator, e_{t+1} is future earnings, P_t is the price that the firm receives for its equity and V_t is the intrinsic value of equity.

When sig_t is of low quality, the market assessment of future earnings conditional on sig_t is irrational. Therefore stock price measures intrinsic value with a mispricing error and the extent of this mispricing depends on the first and second moments of the error term.

3. Sample Selection

To test the implications of the model including the use of negative special items as a "shifting" device to manage core earnings and the market consequences, we collect an initial sample of accounting data and stock returns from the intersection of Compustat and CRSP, for the period 1989−2012. The sample begins in 1989 because accruals are measured directly from the cash flow statement, and the cash flows from operations become available in Compustat after 1988. Equally (value) weighted abnormal returns are size-adjusted returns calculated as the difference between buy-hold returns in excess of the buy-hold returns on the CRSP equally (value) weighted market index. The measurement of returns starts the fourth month of the fiscal year and ends with the third month of the next fiscal year. Delisting returns are used when available, and we substitute zero for missing monthly returns following Campbell et al. (2010). A two-digit SIC code is used to identify industry association and a minimum of 15 non-missing data are required per industry-year group.

The following restrictions are imposed on the data. First, we eliminate firms with sales less than $1 million and missing book values. Second, we assign 0 to missing values of extraordinary items and discontinued operations used to define accruals, and require non-missing values of variables used in measuring expected core earnings. We also require the estimated unexpected core earnings to be non-missing. For the full sample regressions, we assign 0 to special items if they are missing or if the special items are positive (Elliott and Hanna 1996, Dechow and Ge 2006, and MacVay 2006)[27]. The resulting sample is 67,859 (10,185) firm-years (firms).

[27] We require non-zero special items in all regressions that uses a subsample of negative special items firms.

Restatement data are obtained from the Audit Analytics Non-Reliance Restatement database. We use Audit Analytics for the following reasons. First, Audit Analytics covers an entire set of restating firms and indicates the reason for restatements. This allows me to direct the restatement tests to only restatements due to irregularities (intentional misstatements) rather than error-related misstatements that are unintentional (Hennes et al. 2008). Second, Audit Analytics indicates the fiscal years affected by restatements. Other competing databases, such as the GAO database, identify only the year of the restatement announcement, which is an average of two years after the misstatement year (Cheffers et al. 2010). Studies using these databases assume that a misstated year is one that is followed by a restatement over the subsequent two or three years. While the two or three years' range is the average period, identifying the misstated years from Audit Analytics eliminates any possible measurement error associated with this lag assumption.

Restatement data from Audit Analytics begin in 2000. Therefore, we merge Audit Analytics with the Compustat-CRSP sample for the period 2000-2012, and estimate the regressions that involve restatements for this sample period. The resulting sample consists of 38,282 (6,850) firm-years (firms).

We winsorize each accounting continuous variable at its first and 99th percentiles to control for the potential effect of outliers, and report two-tailed significance levels in all regressions. We present descriptive statistics of the main variables before reporting the results of the regressions throughout the paper.

4. The Manager's Decision to Shift Negative Core Earnings to Negative Special Items

4.1. Main Results

The theoretical model suggests that the manager is more likely to take a misclassification decision by moving negative core earnings to negative special items when he observes that the core earnings signal is lower than a certain threshold. To investigate this relation, we initially develop an empirical model that tests for the likelihood that a firm reports negative special items deflated by sales that are higher than the annual cross section mean of negative special items firms after controlling for the firm's poor current and historical performance and other specific factors that are associated with special items reporting. Specifically, we estimate the following regression:

$$\begin{aligned} LARGESP_t = {} & \theta_0 + \theta_1 DIFF_t + \theta_2 SIGMER_t + \theta_3 SIZE_t + \theta_4 AR_t + \theta_5 AR_{t-1} \\ & + \theta_6 FREQ1_t + \theta_7 FREQ2_t + \theta_8 FREQ5_t + \theta_9 ADJBTM_{t-1} \\ & + \theta_{10} \Delta BTM_{t-2\sim t-1} + \theta_{11} ADJROA_{t-1} + \theta_{12} \Delta ROA_{t-2\sim t-1} + \varepsilon_t \end{aligned} \tag{5}$$

where the dependent variable $LARGESP_t = 1$ if firm i reports negative special items deflated by sales that are higher than the cross section mean of non-zero negative special items firms at year t, and zero otherwise[28]. The main variable of interest is $DIFF_t$, defined as reported core earnings at year $t-1$ minus predicted core earnings at year t. This definition assumes that that last year's reported core earnings is the manager's benchmark (core earnings threshold) for what he perceives to be a high or low observed signal of core earnings at year t, and that predicted core earnings act as a proxy for the manager's observed core earnings signal c_t. The choice of this benchmark is motivated by evidence in Schrand and Walther (2000) that managers use the last period's earnings as a benchmark to evaluate current period's earnings. We estimate predicted core earnings as the fitted value from the following core earnings model developed in McVay (2006):

$$CE_t = \varphi_0 + \varphi_1 CE_{t-1} + \varphi_2 ATO_t + \varphi_3 ACC_{t-1} + \varphi_4 ACC_t + \varphi_5 \Delta SALE_t + \varphi_6 NEG\Delta SALE_t + \xi_t \tag{6}$$

All variables in equation (6) are measured similar to McVay (2006). CE_t is core earnings measured as operating income before depreciation divided by sales. ATO_t is assets turnover measured as sales divided by average net operating assets. Net operating assets are calculated as operating assets minus operating liabilities. ACC_t is operating accruals measured as net income before extraordinary items minus cash flow from operations and divided by sales. $\Delta SALE_t$ is sales growth measured as the percentage change in sales, and $NEG\Delta SALE_t$ is the percentage change in sales if sales growth ($\Delta SALE_t$) is negative and 0 otherwise. Following McVay (2006),

[28] Note that special items are conceptually infrequent or unusual earnings items. However, this infrequency at the firm level does not imply infrequency in the cross section. Indeed, one would expect average special items reporting to be indicative of common economic conditions. Reporting above average special items is subject to the firm's reporting incentive and its specific economic conditions.

the core earnings model is estimated out of sample for each industry-year combination and excluding firm i .

We predict the coefficient on $DIFF_t$ to be positive, indicating a positive relation between the likelihood to report above-average negative special items and the difference between the prior year's core earnings benchmark and current year's predicted core earnings. We include other factors that might potentially contribute to the likelihood of reporting large negative special items. These variables control for economic determinants associated with negative special items reporting and are based on prior research. We include a variable that controls for *significant* mergers and acquisitions $(SIGMER_t)$, because some merger-related costs are reported under negative special items, hence *significant* mergers are expected to be positively correlated with *large* negative special items. we measure significant mergers and acquisitions following Baber et al. (2011), but as a dummy variable that is $SIGMER_t = 1$ if annual acquisitions are greater than 20 % of the firm's beginning of the year total assets, and zero otherwise. $SIZE_t$ is the natural log of average total assets (Ahmed and Duellman 2007). We expect the coefficient on $SIZE_t$ to be negative, because Callen et al. (2010) find that reporting negative special items is positively associated with conditional conservatism, and smaller firms are more conservative consistent with their higher level of operational uncertainty. We include abnormal stock returns in the current year (AR_t) and the last year (AR_{t-1}) , measured as the firm's stock return in a given year minus equally weighted market return for the year, in order to control for stock price performance. We expect the coefficients on the abnormal returns variables to be negative, because poor performing firms are found to be more likely to undertake higher restructuring charges (Lee 2014) and one-time write-offs (Francis et al. 1996), which are reported as special items.

We use $FREQ1_t$, $FREQ2_t$ and $FREQ5_t$ to control for the frequency of negative special items recognition, because Elliot and Hanna (1996) find that approximately 50 % of negative special items firms report negative special items in the subsequent period, and that 50 % of those reporting two prior negative special item charges report a third charge. In addition, Johnson et al. (2011) find that the preceding reporting frequency of negative special items over the prior five years can have some implications on subsequent reporting. We measure $FREQ1_t = 1$ if the firm reported negative special items in the previous year and zero otherwise. Similarly, $FREQ2_t = 1$ and $FREQ5 = 1$ if the firm reported negative items two times and five times over the past two and five years, respectively, and zero otherwise. Controlling for prior reporting frequency is important in this setting, because the aim is to capture the currently overstated negative special items that are attributable to the contemporaneous signal on core earnings rather than the negative special items firms' propensity to report consecutive charges. We expect the reporting frequency to be positively, albeit *weakly*, associated with the response variable, because $LARGESP_t$ captures the existence of "above-average" reporting of negative special items rather than "frequent" reporting.

We use the firm's industry-adjusted book-to-market ratio at the year preceding the special item charge $(ADJBTM_{t-1})$, because Francis et al. (1996) find that book-to-market ratios higher than industry peers are positively associated with write-off charges. This is consistent with the assets being impaired when their book values are higher than their economic values which might result in a significant level of negative special items. We measure $ADJBTM$ as the difference between the firm's book-to-market ratio and the cross section mean of the ratio in the firm's industry. In addition to the adjusted level of the ratio, we include the change in the firm's book-to-market ratio in the year preceding the special item charge $(\Delta BTM_{t-2\sim t-1})$. We expect the coefficients on both book-to-market ratio variables to be positive. We also include the firm's industry-adjusted return on asset pre-special items $(ADJROA_{t-1})$ and the change in the firm's return on asset one year before the negative special item $\left(\Delta ROA_{t-2\sim t-1}\right)$. We measure the return on assets as earnings before extraordinary items and discontinued operations minus special items and divided by average assets. We expect the coefficients on both return on asset ratios to be negatively associated with the dependent variable.

In addition to the test in equation (5), the dependent variable is also modified to be either $HI5_t$ or $LO1_t$, to capture extreme special item charges. $HI5_t$ is an indicator variable that takes the value 1 when the firm reports negative special items deflated by sales that are in the fifth quintile of their distribution in the year, and zero otherwise. $LO1_t$ is an indicator variable that takes the value 1 when the firm's negative special items deflated by sales fall in the first quintile in the year, and zero otherwise. Quintiles are formed on the absolute magnitude of (non-zero) negative special items deflated by sales every year. We expect the coefficient on the main variable of interest, $DIFF_t$, to be increasing with $HI5_t$ and decreasing with $LO1_t$. In addition, We predict that the negative impact of $DIFF_t$ on the outcome variable $LO1_t$ is less pronounced than the positive impact of $DIFF_t$ on the outcome variable $HI5_t$, because the test for the misclassification likelihood is more directed to the propensity to hit an upper level of negative special items. All control variables that are expected to be positively (negatively) associated with $LARGESP_t$ are expected to be positively (negatively) associated with $HI5_t$, and negatively (positively) associated with $LO1_t$. Since these regressions examine dichotomous choices, We estimate the regression models using logistic regressions (LOGIT), to mitigate the heteroscedasticity that might be associated with using ordinary least squares linear probability model (OLS-LPM) estimation (Stone and Rasp 1991). However, We also report the OLS-LPM results to see if they are different from the LOGIT results.

Table 1 reports the results of the regressions. Panel A reports the descriptive statistics of the regression variables. In Panel B, We present the coefficient estimates using LOGIT and OLS-LPM. In Panel C, wee provide some further analyses regarding the economic significance of the variables coefficients. In both panels B and C, we highlight the main variable of interest, $DIFF_t$, that we predict to be a major determinant of the misclassification decision, consistent with theory. Model (1) is the regression model with $LARGESP_t$ as the dependent variable. Model (2) and Model (3) are the regression models with $HI5_t$ and $LO1_t$ as the dependent variables, respectively. The logistic regression results in Panel B show significance in the predicted direction of $DIFF_t$ in the three models. According to Model (1), there is a high probability of reporting negative special items above the annual cross section mean when the difference between last year's reported core earnings and current year's predicted core earnings increases. Model (2) shows that the likelihood of reporting extremely high negative special items that are in the fifth quintile of the negative special items distribution also significantly increases with $DIFF_t$. Model (3) shows that extremely low negative special items that are in the first quintile of distribution are negatively associated with $DIFF_t$. All other control variables are consistent with extant research and predictions, except that $\Delta BTM_{t-2\sim t-1}$ is insignificant in all models, and $ADJROA_{t-1}$ is insignificant in Model (3). $DIFF_t$ appears to act as the main influential determinant of reported large negative special items, consistent with a misclassification decision. Moreover, the magnitude of the negative coefficient on $DIFF_t$ is relatively lower in Model (3) consistent with predictions. The OLS-LPM estimations show consistent results to the LOGIT in the three models.

Panel C provides insights into the economic significance of the coefficients and changes in probabilities of the dependent variables when a firm takes different positions with regard to incentives for special items reporting. For each of the three models, we calculate the marginal effects of the coefficients when the model is estimated using actual values as in Panel B, the marginal effects when the model is estimated using standardized variables[29], and the change in propensity to report the different magnitudes of negative special items, according to the models specifications for each variable when the firm moves from the first to the fifth quintile of the variable[30]. We also calculate the probability of the occurrence of the dependent variable when the firm is in the bottom (top) quintiles of the explanatory variables with positive (negative) coefficients[31]. Model (1) shows that when the firm takes on lower quintile values of the explanatory variables, there is a probability of 1.5% for large negative special items reporting. When the firm moves to the upper quintile position, the propensity to report large negative special items increases to 82.4% i.e. there is an 80.9% change in probabilities of large negative special items reporting between the two hypothetical positions. Model (2) shows also consistent results. In addition, moving from the first to the fifth quintile values of each explanatory variable and holding the remaining variables constant at their means reveal that $DIFF_t$ is the main determining factor for the change in the probability of reporting large negative special items in Model (1) and (2). Interestingly, when the focus is on the propensity to report extremely low negative special items in Model (3), the change in probability between the two hypothetical

[29] In standardized variables regressions; continuous explanatory variables are ranked into quintiles, while indicator variables take the values 1 and 0 as in the actual values regressions.

[30] These economic significance analyses are broadly similar to Ashbaugh-Skaife et al. (2006)

[31]The benchmark probability for indicator variables is determined with the zero (one) value of the indicator variable, when it has a positive (negative) coefficient.

positions of the explanatory variables is 56%, and the effect of $DIFF_t$ on the outcome variable becomes relatively less pronounced consistent with prediction.

[Insert Table 1 here]

Figure 1 shows an inter-temporal analysis of negative special items for the years surrounding signed $DIFF_t$. In Panel A (B), the event year 0 is the year in which $DIFF_t$ is positive (negative). The plots show negative special items (deflated by sales) in the three years before and after the event year. Figure 1 Panel A shows that negative special items are relatively stable three years before the year of positive $DIFF_t$. At the event year, there is an upward spike in negative special items, which is followed by a monotonic decrease in negative special items over the following three years. This result is consistent with a higher motivation to move more negative core earnings to negative special items, when the prior year's reported core earnings are higher than the current year's predicted core earnings, which results in a larger magnitude of reported negative special items at the event year.

Figure 1 Panel B shows that negative special items monotonically increase up to the event year of negative $DIFF_t$. However, at the event year, there is a downward spike in negative special items. Over the three years following the event year, the monotonic increasing pattern of negative special items continues. This result is consistent with less motivation to move negative core earnings to negative special items, when the prior year's reported core earnings are less than the current year's predicted core earnings, which yields a smaller magnitude of negative special items.

[Insert Figure 1 here]

4.2 Is the Manager Decision to Shift Negative Core Earnings to Negative Special Items Discretionary or Manipulative?

Thus far, results reveal that $DIFF_t$ is an influential determinant of the probability to report large negative special items. We now further investigate whether the extreme reporting strategy is discretionary and within-GAAP or manipulative and represents a GAAP violation. According to the model, accounting misclassification is indicative of the degree of compliance with accounting standards and the manager's private knowledge of the core earnings signal that motivated the misclassification. To align the empirical analysis as closely as possible with the model, we focus only on a cutoff point for compliance with GAAP such that $GAAPCOMPLIANCE = 1$ if the firm's fiscal year is not a misstated year, and zero if the firm's fiscal year is a misstated year that has been subsequently restated (due to irregularities or fraud). As mentioned in the data section, the test here is restricted to years after 2000, because restatements data from Audit Analytics are only available after 2000[32].

We estimate the following regression:

$$HI5_t = \eta_0 + \eta_1 GAAPCOMPLIANCE_t + \eta_2 DIFF_t + \gamma CONTROLS \qquad (7)$$

where $CONTROLS$ are the same set of controls used in equation (5).

We predict the coefficient on $GAAPCOMPLIANCE_t$ to be positive if the extreme reporting strategy of negative special items complies with the accounting standards. In other words, the manager uses his discretion and classifies some negative core earnings as negative special items, which increases the negative special items magnitude, but this classification choice is within the limits allowed under accounting standards. We predict the coefficient on $GAAPCOMPLIANCE_t$ to be negative if the reporting strategy is more likely to represent GAAP violation.

As a robustness check, we replace $HI5_t$ with an indicator variable, $MEANSI_t$, which is equal to 1 if reported negative special items deflated by sales are within a ratio of 30 % higher or lower than the annual cross section mean of non-zero negative special items firms, and zero otherwise. The aim is to ensure that results of equation (7) are exclusive for a large negative special items strategy that is more likely to reflect accounting misclassification rather than normal special items reporting. Therefore, we predict lower significance for the coefficient on $GAAPCOMPLIANCE_t$ in this case. Table 2 reports the results of these models using logistic regressions.

[32] The use of an indicator variable $GAAPCOMPLIANCE$ is meant to proxy for firms that do not misreport their financial statements due to irregularities or fraud and regardless of the cause of misstatement. The indicator variable partitions firms on the basis of compliance with GAAP and thus firms that restate their financial statements for reasons other than expense misclassification are pooled together as violators. Interpreted with caution, the results here investigate the tendency of complying firms versus manipulating firms to report large negative special items.

Table 2 Panel A reports results of the compliance of extreme special items reporting with accounting standards. The results reveal that the coefficient on $GAAPCOMPLIANCE_t$ is significantly negative ($\eta_1 = -0.264, t - statistics = -3.161$ with industry-year fixed effects, and $\eta_1 = -0.187, t - statistics = -2.35$ without industry-year fixed effects). This suggests that the outcome strategy of extreme negative special items reporting is more likely associated with firms not complying with accounting standards. The coefficient on $DIFF_t$ remains significantly positive at a relatively similar magnitude ($\eta_2 = 2.398, t - statistics = 10.58$ with industry-year fixed effects, and $\eta_2 = 2.179, t - statistics = 9.64$ without industry-year fixed effects).

Table 2 Panel B reports results of the compliance of normal special items reporting with accounting standards. The results reveal that the coefficient on $GAAPCOMPLIANCE_t$ is lower and insignificant ($\eta_1 = -0.095, t - statistics = -0.92$ with industry-year fixed effects and $\eta_1 = -0.055, t - statistics = -0.54$ without fixed effects). Moreover, the coefficient on $DIFF_t$ is negative and insignificant ($\eta_2 = -0.046, t - statistics = -0.25$ with industry-year fixed effects, and $\eta_2 = -0.086, t - statistics = -0.41$ without industry-year fixed effects). These findings indicate that the GAAP violation results in Table 2 Panel A are specific for a reporting strategy of large negative special items that is consistent with negative core earnings misclassification.

[Insert Table 2 here]

5. Decomposition of Negative Special Items: Separating Accounting Misclassification from Economics

5.1 The Decomposition Approach

McVay (2006) finds evidence that accounting misclassification results in a positive association between current unexpected core earnings and current negative special items. She argues that the negative special items' "positive" coefficient captures the average degree of misclassified operating expenses in special items. Following Abdalla and Clubb (2015), we split negative special items into two additive components. The first component represents negative core earnings that are misclassified in the income statement (accounting misclassification). The second component represents special items that reflect unusual events (economics). To do this, we use the same core earnings expectation model by McVay (2006) as in previous sections to proxy for expected core earnings, and regress current unexpected core earnings on current negative special items (measured in absolute terms here) for each industry-year group. Determination of industry membership by a two digit SIC code gives smaller groups with more spread, which enhances the accuracy of the measurement approach[33]. Then, we set all negative industry-year coefficients to equal zero, because negative coefficients are consistent with negative special items being reported in these industry-year groups due to poor economic performance rather than misclassification (approximately 45 % of coefficients are negative). In addition, instead of setting all estimated positive coefficients that are higher than one to be zero as in Abdalla and Clubb (2015), we alternatively set them to be equal to one (these coefficients represent only 4% of all estimated coefficients)[34] . Finally, we multiply the resulting industry-year positive coefficients by the actual negative special items of firms in the related industry-year group. This produces a firm-year measure of misclassified negative core earnings (that is negative by construction to represent the expense nature of the earnings component), denoted MCE_t. We subtract this measure from reported negative special items, SP_t, to estimate real negative special items that reflect economic conditions rather than accounting misclassification, denoted RSP_t.

Figure 2 displays the mean industry-year coefficients over the sample period. The results show that the coefficient sign varies. On average, this is consistent with reporting negative special items to accommodate misclassified negative core earnings (positive coefficient), or as a result of poor performance (negative coefficient). The decomposition approach aims to measure misclassified earnings and back out real special items that are not used to manage core earnings.

[Insert Figure 2 here]

[33] As mentioned earlier, each industry-year group is required to have at least 15 non-missing observations.
[34] Both methodological choices are consistent with the notion that classification shifting is bounded by 100% of negative special items. One approach chooses to exclude coefficients higher than 100%, while the other one sets them at the maximum bound of shifting. All following empirical results are similar under both approaches.

5.2 Validation of the Decomposition Approach and Prediction of Annual Report Restatements

The empirical evidence so far reveals that firms are less (more) likely to report larger negative special items when their financial statements comply with (violate) the accounting standards. This suggests that the negative special items reporting strategy might contain information that can be used to identify the misstatement years. If MCE_t captures information about the misuse of negative special items to conceal negative core earnings, and RSP_t is a measure of real special items that are not related to earnings management, we expect the association between negative special items and the probability to restate an annual report to be attributable to the MCE_t component of negative special items, after controlling for factors that might be related to restatements. We estimate the following regression:

$$\begin{aligned} RESTATE_t = \kappa_0 + \kappa_1 SP_t + \kappa_2 \Delta REC_t + \kappa_3 \Delta INV_t + \kappa_4 SFASSET_t + \kappa_5 \Delta CSALE_t \\ + \kappa_6 \sigma_{SALE} + \kappa_7 ABEMP_t + \kappa_8 \Delta ROA_t + \kappa_9 AR_t + \kappa_{10} AR_{t-1} \\ + \kappa_{11} BTM_t + \kappa_{12} LEV_t + \zeta_t \end{aligned} \tag{8}$$

where $RESTATE_t$ is an indicator variable that is equal to one if firm i fiscal year t is misstated and subsequently restated due to accounting irregularities or fraud, and zero otherwise. SP_t is the main variable of interest. We first estimate the regression with SP_t, and then replace SP_t with its underlying components MCE_t and RSP_t. We also estimate the regression by replacing SP_t with only an indicator variable $MCEind_t$ that is equal to one if MCE_t is non-zero and zero otherwise, as a robustness check. We measure negative special items and their two components in absolute terms in these regressions. Most control variables are taken from Dechow et al. (2011) and Hribar et al. (2014). ΔREC_t is the change in receivables divided by average total assets. ΔINV_t is the change in inventory divided by average total assets. $SFASSET_t$ is the percentage of soft assets and defined as total assets minus cash and PPE, divided by total assets. The variables ΔREC_t and ΔINV_t are accruals components that improve sales growth and gross margin respectively, when misstated. $SFASSET_t$ controls for the accounting flexibility to use net operating assets to meet short term earnings expectations (Barton and Simko 2002). $\Delta CSALE_t$ is the percentage change in cash sales where cash sales are defined as sales minus change in accounts receivable. This cash sales measure controls for the firm's change in sales that is not subject to accruals management. σ_{SALE} is a measure of sales volatility and defined as the standard deviation of the firm's rolling five-year net sales, divided by average total assets (minimum of three non-missing observations). $ABEMP_t$ is the abnormal change in employees and defined as the percentage change in the number of employees divided by the percentage change in total assets. Dechow et al. (2011) use the $ABEMP_t$ measure to capture information about firms reducing employee headcount and overstating assets to cover deteriorating financial performance. ΔROA_t is the change in return on assets pre-special items and defined as earnings before extraordinary items and discontinued operations less special items, divided by average total assets. We include AR_t and AR_{t-1} to control for stock price performance and BTM_t to control for optimistic expectations embedded in the firm's stock valuation, which can be a motive to misstate earnings in order to maintain overvaluation. LEV_t is the firm's leverage and defined as the sum of short term debt and long term debt, divided by average total assets. Leverage controls for the effect of debt contracting on misstating earnings in order to satisfy financial covenants.

Table 3 Panel A shows the descriptive statistics of the main variables. We estimate the regressions using OLS-LPM and LOGIT and report the results in Table 3 Panel B. For the sake of brevity, we report only the marginal significance from the logistic regressions[35]. Table 3 Panel B results reveal that the coefficient on SP_t is significantly positive (0.061, t =2.64)[36]. This indicates that a proportion of reported negative special items is associated with the occurrence of restatements. When the two components of negative special items are used in lieu of reported negative special items in the regression, the results show that the coefficient on the MCE_t component is significantly positive (0.492, t =2.15) and the RSP_t component does not load in the regression (0.029, t=1.07). When only the $MCEind_t$ indicator variable is used to proxy for the incidence of negative core earnings misclassification, the coefficient on $MCEind_t$ is positive and

[35] All OLS-LPM and LOGIT coefficients results are very similar.
[36] Since the OLS-LPM and LOGIT-MEM results in Table 4 are highly consistent, we choose to refer to the OLS-LPM in text, unless otherwise explicitly stated.

significant (0.014, *t*= 3.17). The economic significance from the LOGIT estimation is also highly consistent with the OLS-LPM results. The control variables' results are fairly consistent with those in Hribar et al. (2014)[37]. These regression results validate the decomposition approach by showing that *MCE* is the respective component of negative special items that reflects earnings management.

[Insert Table 3 here]

6. The Forecast Information Content of Misclassified Negative Core earnings and the Market Perception of Misclassification

Equation (4) expresses a relation between the market assessment of the earnings process relative to the actual earnings process and a resulting equality of stock price and intrinsic value. The researcher cannot directly observe the market assessment or measure the intrinsic value without error, but can instead observe the historical forecasting relevance of earnings variables with respect to future earnings, as well as stock prices. Assuming that stock prices impound the market assessment, a comparison between the earnings variable's ability to forecast future earnings and its perceived valuation relevance with regard to stock returns helps to draw some inferences regarding the *ex-ante* market assessment. We estimate the following forecasting and pricing models[38]:

$$E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega_{2,3}^{*} SP_t + \omega_4 BV_t + error_{t+\tau} \tag{9}$$

$$E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega_2 MCE_t + \omega_3 RSP_t + \omega_4 BV_t + error_{t+\tau} \tag{10}$$

$$AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha_{2,3}^{*} \Delta SP_t + \alpha_4 \Delta BV_t + error_{t+1} \tag{11}$$

$$AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha_2 \Delta MCE_t + \alpha_3 \Delta RSP_t + \alpha_4 \Delta BV_t + error_{t+1} \tag{12}$$

$E_{t+\tau}$ is earnings for period $t+\tau$ divided by sales, CE_t is core earnings measured as operating income before depreciation divided by sales, SP_t is reported negative special items divided by sales, MCE_t is misclassified negative core earnings, RSP_t is real special items, BV_t is ending book value divided by sales, and AR_t is abnormal returns measured as stock return for firm i in

[37] Although Hribar et al. (2014) report coefficients' results when the dependent variable includes only accounting restatement, fraud, or comment letter; our results are reasonably consistent with their results.

[38] Although we present results from the price change (return) model rather a price level model; using the natural logarithm of stock prices measured three months after the end of the fiscal year and the accounting variable levels give qualitatively similar results.

year t minus equally weighted market return for year t[39], and Δ denotes the change in variables between years t and $t-1$.

We estimate both the forecasting and pricing models using OLS. The earnings dependent variable is measured using three earnings metrics. We use abnormal earnings (earnings before extraordinary items and discontinued operations minus 12% of beginning of the period book value)[40] because abnormal earnings represent the *excess value* created, which play a central role in equity valuation (Ohlson 1995, O'Hanlon and Peasnell 2002), earnings before extraordinary items and discontinued operations (earnings hereafter), and earnings before special items. The last earnings measurement complements the results by showing whether the relation between misclassified negative core earnings and future profitability holds after removing special items from the profitability measure. We also estimate the earnings model for a forecast horizon up to three years, because we expect firms that temporarily hide negative core earnings in the current period to have poorer performance over the next few years. In addition, an earnings variable's ability to forecast only one-year ahead earnings might not be the only value relevance dimension when setting stock prices.

In the following tests, we use two alternative research designs similar to Doyle et al. (2003) with regard to the inclusion/exclusion of zero negative special items observations in/from the sample. Including the zero observations improves the analysis by including estimates of the impact of other variables in the entire sample. Excluding the zero observations provides direct evidence with regard to the magnitude of the non-zero negative special items and rules out the possibility that the results are driven to some extent by the decision to have negative special items in a given year[41]. The results appear to be robust to both alternative research designs. We report the forecasting results in Table 4, and the pricing results in Table 5.

Table 4 Panel A displays the descriptive statistics of the sample. Table 4 Panel B shows estimates of the earnings forecast model without negative special items decomposition. The results show that both reported core earnings and negative special items have different

[39] Results do not change when we use value weighted abnormal returns.
[40] We assume a fixed 12% cost of capital consistent with Barth et al. (1999).
[41] Doyle et al. (2003) and McVay(2006) use the same alternative research designs in treating zero Pro-forma exclusions and negative special items, respectively.

information content with regard to future earnings over all earnings windows[42]. There is a decreasing pattern for both the core earnings and negative special items coefficients, as the earnings horizon expands. Although the coefficient of negative special items decreases over longer windows, it does not lose significance except in the three-year window when the earnings forecast variable is measured before special items.

We now test the same forecast models after negative special items decomposition. Table 4 Panel C shows the results of estimating the models after negative special items are decomposed into their components. The results reveal that all earnings variables have some information content with regard to one-year ahead abnormal earnings, however, the equality of the earnings coefficients cannot be accepted using Wald test (untabulated). Interestingly, the two components of special items look so different now. While the coefficient on misclassified negative core earnings has an increasing pattern as the abnormal earnings window expands, the coefficient on real negative special items has a decreasing pattern and loses significance. In addition, both core earnings and misclassified negative core earnings forecast one year-ahead abnormal earnings as if they are the same earnings variable and their coefficients are significantly indifferent $[F-value=0.02, P-value=0.892]$.When the abnormal earnings window increases, misclassified negative core earnings provide some information beyond core earnings and the difference between both variables coefficients becomes marginally significant $[F-value=4.38, P-value=0.036$ for the one-year horizon] and $[F-value=3.91, P-value=0.0480$ for the two-year horizon]. This is consistent with the prediction that temporary shifting in the current period is associated with deterioration in profitability in future periods[43]. Similar results are obtained when earnings before extraordinary items and discontinued operations are used as the earnings forecast variable, except that the increasing pattern of the misclassified negative core earnings coefficient is weaker. In addition, although the misclassified negative core earnings coefficient is still relatively higher than the core earnings coefficient, the difference between the coefficients is insignificant in all earnings

[42] Untabulated results using Wald test show significant differences between the core earnings and negative special items coefficients in all regressions over the three earnings windows.

[43] Abdalla and Clubb (2015) show analytically some conditions under which misclassified negative core earnings act as a bad news signal for poor performance besides their role as an earnings variable, which drives their coefficient relatively higher than that of reported core earnings, consistent with this incremental informational role. Their empirical analyses using only one-year ahead abnormal earnings show that this bad news signal is insignificant. We find here that it can be marginally significant when the earnings horizon expands beyond one year.

windows. Moreover, when earnings before special items are used, there is still a significant association between misclassified negative core earnings and future earnings. This ensures that the association of misclassified negative core earnings with future earnings is not only attributable to the possibility of serial shifting (i.e. the persistence of misclassified negative core earnings when firms serially shift in subsequent periods), but also to the forecast of future *core* profitability. This is consistent with the original nature of misclassified earnings as core earnings rather than their representational form as special items in the income statement. Furthermore, the results show that real special items have their smallest coefficient with regard to one year-ahead earnings in this latter case, and that the coefficient loses significance earlier once the forecast horizon increases to two years (in the first two earnings regressions it loses significance in the three-year horizon).

In Table 4 Panel D, we estimate the earnings forecast model using two subsamples of special items firms; namely a subsample of firms with non-zero negative special items and a subsample of firms with non-zero misclassified negative core earnings. We use the future earnings forecast measure that excludes special items[44]. The results show that the association of misclassified negative core earnings with future earnings increases as the sample is restricted to negative special items firms and further to negative special items shifters.

These results expand the evidence in Abdalla and Clubb (2015) to show that the misclassified negative core earnings measure has more than one forecasting relevance dimension with regard to future earnings. Since misclassified negative earnings are "negative" data values, their positive coefficients here are consistent with lower profitability over future years for firms that shift certain amounts of their operating expenses in the current period.

[Insert Table 4 here]

Moving to the pricing models, we test the pricing model with reported negative special items (no-decomposition) in Table 5 Panel A, and the pricing model with the two negative special items components in Table 5 Panel B. The results in Panel A show that the changes in both core earnings and negative special items are incorporated in stock returns with significantly different weights $[F-value=6.88, P-value=0.008]$ consistent with their forecasting relevance

[44] Results are consistent using the three measures of future earnings.

in the earnings forecast test. When reported negative special items are replaced with their two components in Panel B, an interesting result emerges. Unlike the forecast test results, the coefficient on real special items is similar to that on reported negative special items in the no-decomposition scenario, and misclassified negative core earnings also have the same coefficient magnitude, albeit rather insignificant. This discrepancy from the forecasting results suggests that the market does not appear to understand the implications of negative core earnings misclassification on future earnings and ignores the informational heterogeneity between the negative special items components. The market assessment of the earnings process does not appear to adjust for the fact that negative core earnings misclassification in the current year has negative impact on future profitability.

We subsequently limit the sample to firms that reported negative special items in years t and $t-1$, and, further, to negative special items firms that misclassified negative core earnings in years t or $t-1$, or misclassified in both years. Table 5 Panel C presents the results of the three subsample tests. Similar to the full sample test results, misclassified negative core earnings do not appear to be fully impounded in stock returns relative to their superior forecasting impact on future earnings that persists (or even increases) over a horizon up to three years. Moreover, restricting the sample to negative special items firms and more specifically to firms that misclassified negative core earnings decreases the magnitude of the coefficient on misclassified negative core earnings which is still insignificant across all subsamples.

[Insert Table 5 here]

7. Negative Core Earning Misclassification Signals

7.1 Informative and Noisy Misclassification Signals

Theoretically, mispricing occurs when the market expectation of the earnings process is a biased estimate of the actual process. In the context of earnings misclassification, this bias is likely to be attributable, in part, to noise and garbling in the misclassification signals processed by investors when setting prices, i.e. $E_t^m(e_{t+1} \mid sig_t) \neq E(e_{t+1} \mid \lambda_t) \mapsto P_t \neq V_t$.

We distinguish between two types of misclassification signals: an informative misclassification signal and a noisy misclassification signal. We define a misclassification signal as being "informative", when the predictive ability of negative special items for future earnings improves in line with the signal. This is because transferring operating (recurring) expenses to negative special items increases the core element of special items and therefore is expected to increase the predictive ability of special items. This forecast information content is a function of the proportion of operating expenses in special items, such that the more the negative special items are contaminated with operating expenses, the higher the predictive ability the special items have, and this is signified by the magnitude of the informative signal. With regard to valuation, the contemporaneous association between stock returns and negative special items conditional on the informative misclassification signal depends on investors' perception of the signal. In contrast, a misclassification signal is "noisy" when it leads to a monotonic change in the contemporaneous association of stock returns with negative special items that is in line with the signal but inconsistent with negative special items predictability for future earnings.

This suggests that the match between the investors' perception of the misclassification signal, which is reflected in stock prices, and the improvement in the negative special items predictability of future earnings relative to the signal, infers whether investors are reacting to noisy or informative signals of misclassification. This intuition formulates the empirical tests in this section.

To operationalize the misclassification signals idea, we hypothesize, building on the previous empirical results, that one informative signal of the occurrence of misclassification is $DIFF_t$. The logistic regression results showed a propensity to report large negative special items in relation to an increasing level of $DIFF_t$, which is consistent with a shift of negative core earnings to negative special items. If $DIFF_t$ signifies the movement of operating expenses to negative special items with a sufficient degree of accuracy, we predict an improvement in the predictability of negative special items for one year-ahead earnings across portfolios formed on $DIFF_t$. If investors do not rationally process this informative misclassification signal, the improvement in negative special items predictability is not impounded in stock prices, i.e. stock prices do not react to information in the signal correspondingly.

On the other hand, if investors naively infer the extent of misclassification from the earnings report, we expect stock prices to respond relatively to a reporting signal in the income statement.

If this signal is noisy, negative special items predictability should not exhibit a similarly consistent monotonic pattern across portfolios formed on the noisy signal. A hypothetical reporting signal of misclassification could be an increasing level of operating income before special items when the firm reports negative special items in a given year, denoted $OIBD_t$. We investigate the quality of this crude reporting signal in our test, because Fairfield et al. (2009) find that negative special items are more likely to include operating expenses when firms have high rather than low core profitability.

7.2. Misclassification Signals: Testing Methodology

The misclassification signals test is formed as following. First, we construct five portfolios on the basis of the signals, $DIFF_t$ and $OIBD_t$. Second, we estimate the earnings forecast model, which incorporates reported negative special items with no decomposition in equation (9), per each portfolio of the signal. We use OLS portfolio regressions and the three earnings dependent variables as before (abnormal earnings, earnings, and earnings before special items). We report on the coefficient of negative special items and the difference between the core earnings and negative special items coefficients across all portfolios. A monotonic increasing pattern of the negative special items coefficient in relation to the signal portfolio rank indicates that the negative special items impact on future earnings corresponds with the signal. Hence, the signal *reliably* infers the transfer of negative (recurring) core earnings to negative (nonrecurring) special items, which in turn enhances the negative special items predictability. A monotonic decreasing pattern of the difference between core earnings and negative special items coefficients in relation to the signal portfolio rank signifies the degree of convergence between core earnings and negative special items in their predictive ability as the proportion of negative (recurring) core earnings increases in negative special items because of the misclassification. In other words, the negative special items become more core. According to theory, we predict only the informative signal, $DIFF_t$, to exhibit these consistent patterns.

To provide more evidence on the improvement in the forecast information content of negative special items in correspondence with the misclassification signal, we group the bottom (top) two signal portfolios in a lowest (highest) signal portfolio and estimate the adjusted R^2 for the earnings forecast model per the lowest and highest portfolio groups. Then, we use a

Shorrocks-Shapley decomposition of the model-adjusted R^2 (Shapley 1953, Shorrocks 1982 & 2013) to investigate if the *marginal* contribution of negative special items towards the total adjusted R^2 increases when moving from the lowest to the highest signal portfolio[45,46]. We predict an improvement in the negative special items-decomposed R^2 only when the misclassification signal is informative. We also estimate the impact of a one-standard deviation change in negative special items on future earnings in the lowest and highest portfolio groups to test the economic significance of negative special items predictability between the two groups.

Third, we estimate the pricing model, which has no negative special items decomposition in equation (11), per each portfolio of the five signal portfolios. We report on the ERC (earnings response coefficient) of negative special items and the difference between the ERCs of core earnings and negative special items across the signal portfolios. We predict that investors respond to the reporting misclassification signal, $OIBD_t$, when pricing negative special items. Therefore, we expect a monotonic increasing pattern for the ERC of negative special items and a monotonic decreasing pattern for the difference between the ERCs of core earnings and negative special items in relation to the $OIBD_t$ portfolio rank. If these pricing results do not correspond with a consistent improvement in the predictive ability of negative special items relative to the $OIBD_t$ portfolio rank, we conclude that stock prices react to information in a noisy misclassification signal. In this case, we also expect to observe no clear pattern for the change in the association between stock returns and negative special items relative to the $DIFF_t$ signal.

7.3 Misclassification Signals: Results

7.3.1 The Informative Signal Results

Figure 3 reports on the variation of the forecast information content of negative special items across the $DIFF$ portfolios. Panel A shows the negative special items forecasting coefficient estimates, and Panel B shows the difference between the core earnings and negative special items forecasting coefficients. Panel A plots indicate that negative special items coefficients

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[45] Results are qualitatively similar when we estimate the *Shorrocks-Shapley* decomposed R^2 for each portfolio of the five portfolios in the subsequent tests. We choose to present the extreme group portfolio results.
[46] To our knowledge, this is one of the first papers that applies the *Shorrocks-Shapley* decomposition in accounting research.

display a monotonic increasing pattern with *DIFF*. The forecasting ability of negative special items increases from 0.196 to 0.396 with respect to future abnormal earnings, 0.219 to 0.437 with respect to future earnings and 0.029 to 0.223 with respect to future earnings excluding special items. The increase in the negative special items coefficient is approximately 100% in forecasting abnormal earnings and earnings, and exceeds 600% in forecasting earnings before special items. This is consistent with negative special items being more contaminated with negative core earnings that improve the special items forecasting ability. The major improvement of 600% in the coefficient of negative special items indicates that "a major structural change" takes place in the fundamental composition of the negative special items between portfolio 1 and portfolio 5, which allows the special items to forecast recurring earnings that exclude special items.

Panel B plots show a convergence between the forecasting ability of core earnings and negative special items with the *DIFF* portfolio rank. The distance between the core earnings and negative special items coefficients with respect to all earnings forecasts decreases monotonically with *DIFF*.

[Insert Figure 3 here]

Table 6 presents the results of the *Shorrocks-Shapley* decomposition of the adjusted R^2 of the earnings forecast model. For ease of exposition and the focus on negative special items, we show only the *Shorrocks-Shapley* values pertaining to negative special items. In addition, Table 6 also reports the economic significance of the negative special items coefficient. We present results for the lowest and highest portfolio groups as described in the test methodology. Panel A, B and C show the estimation results for forecast of abnormal earnings, earnings, and earnings before special items, respectively.

Table 6 Panel A reveals that the negative special items' marginal contribution to the model R^2 increases from 3.71% to 7.30%, although the model R^2 decreased from 64% to 57% (i.e. an approximate 100 % in the negative special items' contribution to the model R^2). The increase in the *Shorrocks-Shapley* value between the lowest and highest portfolios signifies the gain in the negative special items' marginal contribution to the explanatory power of the earnings forecast model in relation to the *DIFF* signal. The decrease in the model R^2 in the highest portfolio, which represents a drop in the predictive ability of the model, can be linked to a loss in the forecast information content of core earnings that are "artificially" boosted by the misclassification. This is because core earnings are supposed to contribute the most to the model R^2 .

In untabulated results, the core earnings' marginal contribution to the model R^2 declined from 59.15% in the lowest portfolio to 55.08 % in the highest portfolio. The book value's marginal contribution is approximately the same between the portfolios: 37.14 % in the lowest portfolio and 37.62 % in the highest portfolio. This result is interesting in itself, because it shows a relation, as one would expect, between only the accounting variables that are affected by the misclassification (core earnings and negative special items but not book value) and the misclassification signal. We conclude that although the negative special items' contribution to the model R^2 increases by an approximately similar drop in the core earnings' contribution, which resembles a transfer of forecast information from core earnings to special items, this transfer results in a loss of information due to an accompanying adverse effect on the overall predictive power from the illusionary and unmaintainable increase in core earnings[47].

With regard to economic significance, Table 6 Panel A shows that the impact of a one-standard deviation change in negative special items on one-year-ahead abnormal earnings is 168 basis points in the lowest *DIFF* portfolio and increases to 526 basis points in the highest *DIFF* portfolio.

Table 6 Panel B and Panel C show similar results for the increase in the negative special items *Shorrocks-Shapley* values and economic significance between the portfolio groups. In Panel B (C), the *Shorrocks-Shapley* value of negative special items is 4.28% (3.30%) in the lowest portfolio and increases to 9.74% (6.55%) in the highest portfolio. A one-standard deviation increase in negative special items reduces future earnings (earnings excluding special items) by 179 (47) basis points in the lowest portfolio and 566 (295) basis points in the highest portfolio.

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[47] Note that the *Shorrocks-Shapley* values are an additive decomposition of the total R^2 of the model. The decomposition approach shows each variable's relative contribution to the R^2 . A model with 5% or 80% R^2 will have decomposed R^2 that, for all variables, sum to 100%.

Based on these forecasting results, we conclude that $DIFF_t$ is an informative misclassification signal that indicates the likelihood of negative core earnings transfer to negative special items. This transfer changes the fundamental structure and forecast information content of negative special items, such that it increases the proportion of the core composite of special items and hence the special items predictability of future (value-added) profitability.

[Insert Table 6 here]

With regard to the pricing results, Figure 4 reports on the contemporaneous association of stock returns with negative special items across the $DIFF$ signal portfolios. The results show that the value relevance of negative special items, as per their ERC, exhibits a concave relation with the informative signal portfolio rank. The ERC increases in portfolios $(1-3)$ and decreases in portfolios $(3-5)$. In addition, the pricing convergence with core earnings, measured as the difference between the ERCs of core earnings and negative special items, increases between portfolios (1−2), decreases in portfolios (2−4) and then increases again in portfolio (5). The return associations do not correspond with the improvement in negative special items predictability as documented by the forecasting results. Stock prices appear not to adjust to the improvement in the forecast-relevant information of negative special items across the $DIFF$ portfolios, because of the market inability to fully infer the misclassification, as predicted by theory.

[Insert Figure 4 here]

7.3.2 The Noisy Reporting Signal Results

Figure 5 reports on the variation of the forecast information content of negative special items across the $OIBD$ portfolios. Panel A shows the negative special items coefficient, and Panel B shows the degree of forecasting convergence between core earnings and negative special items, across the signal portfolios. The results reveal no consistent increasing (decreasing) patterns in Panel A (B). In Panel A, the negative special items coefficient decreases between portfolios (1−2), increases between portfolios (2−3) and then decreases again in portfolios (3−5). In Panel B, the difference between core earnings and negative special items coefficients decreases in portfolios (1−3) and then increases afterwards.

[Insert Figure 5 here]

Table 7 shows the results of the *Shorrocks-Shapley* decomposition, and economic significance of negative special items, between the lowest and highest *OIBD* portfolios. Panels A, B, and C show the estimation results with respect to forecasting abnormal earnings, earnings, and earnings before special items, respectively. Panel A results reveal that the model R^2 decreased from 62% to 20% between the two portfolios, but the negative special items marginal contribution to the model R^2 remains relatively the same. This implies that the negative special items' predictive ability of value-added profitability does not change relative to the reporting signal. The economic significance of the negative special items coefficients even decreases from 726 basis point in the lowest portfolio to 229 basis point in the highest portfolio. Panel B results show a substantial drop in the model R^2, an increase in the *Shorrocks-Shapley* value, and a decrease in economic significance. Panel C shows a substantial drop in the model R^2, a decrease in the *Shorrocks-Shapley* value, and a decrease in economic significance.

The forecasting results reveal that the negative special items predictability in relation to the *OIBD* portfolios look so different from that in relation to the *DIFF* portfolios. While the *DIFF* signal manifests itself in a consistent increasing predictive ability of negative special items, *OIBD* does not signal any improvement in the predictability of negative special items. In most results, negative special items even appear to lose rather than gain forecast-relevant information by the *OIBD* signal. This suggests that reporting an escalating level of operating income before special items when the firm has negative special items does not necessarily imply that the negative special items contain more negative core earnings to the extent that justifies the enhancement of operating income before special items.

[Insert Table 7 here]

To investigate whether the market perceives the "misclassification" information in negative special items by $OIBD_t$ to be of lower or higher quality, Figure 6 reports on the ERC of negative special items in Panel A, and the pricing convergence with core earnings in Panel B. The results in Panel A indicate a monotonic increase in the ERC of negative special items. The coefficient increases monotonically in portfolios (1−4) from 0.287 to 0.813, but only decreases to 0.593 in portfolio (5). Panel B also indicates a monotonic decrease in the difference between core earnings and negative special items coefficients over all portfolios except for portfolio (1).

These results are, on average, consistent with stronger association between stock returns and negative special items conditional on the reporting signal, and that this reporting signal does not provide useful information about the composition and predictability of negative special items. The results reveal that firms improving their operating income before special items and reporting negative special items in the same year are not necessarily misclassifying their negative core earnings. Therefore, the misclassification information by $OIBD_t$ is noisy and should be disregarded when setting prices. However, it appears that the market reacts to this reporting signal when pricing negative special items due to its restricted ability to infer the informative signal, which in turn, is likely to induce noise in stock prices.

[Insert Figure 6 here]

8. Conclusion

Prior research documents that the classification of earnings components in the income statements has significant impact on the market response to earnings (Lipe 1986, Ohlson and Penman 1992, Bartov and Mohanram 2014). We extend this research by studying a special case when this classification is a manifestation of the manager's "preferred classification" of earnings-line items rather than "economic reality". In this sense, the placement of earnings in the income statement represents a misclassification of earnings components, such that an income statement classification pools earnings numbers that have economically different content. We study how the classification of recurring earnings as nonrecurring earnings induces a "hidden" core element in nonrecurring earnings. More specifically, we focus on the misclassification of negative core earnings as negative special items in the income statement.

We document that extremely large negative special items in the income statement are positively associated with the difference between reported core earnings in the prior period and expected core earnings in the current period, after controlling for economic conditions. We interpret this as the manager misclassifying some negative core earnings as negative special items when his expectation of core earnings falls below his benchmark. The results reveal that the manager's misclassification strategy represents GAAP violation rather than allowable discretion.

Applying a decomposition approach on negative special items to disentangle the misclassified component from real special items yields two earnings components with different accounting properties. The results show that the association between negative special items and subsequent restatements of financial statements is mainly due to the identified component of misclassified earnings. Additionally the forecasting coefficient of the misclassified component is similar to that of reported core earnings. However, stock prices do not appear to fully reflect the information contained in the misclassified component.

We investigate the contemporaneous association between stock returns and reported negative special items conditional on signals of misclassification. We document that the market is not able to process an informative misclassification signal, which is consistent with enhancements in negative special items predictability of future earnings, but rather relies on a noisy reporting signal, which does not signify the movement of negative core earnings to negative special items. For example, we find that the negative special items persistence increases and the distance between the core earnings persistence and the negative special items persistence decreases in relation to the informative misclassification signal. Moreover, the economic significance of negative special items predictability of future earnings increases from 179 to 566 basis points and the *Shorrocks-Shapley* value of negative special items increases from 4.28% to 9.74%, when moving from the lowest informative signal portfolio to the highest informative signal portfolio. Nevertheless, stock return association with negative special items does not change accordingly. In contrast, when we investigate the stock return association with negative special items conditional on a reporting misclassification signal deduced from the income statement, we find evidence of negative special items being priced in correspondence with the reporting signal. This suggests that investors rely on the reporting signal to infer the misclassification. However, the negative special items predictability does not improve in line with the reporting signal.

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APPENDIX

Variable Definitions

Label	Description	Measurement
$LARGESP_t$	Large negative special items indicator variable	Equal to one when the firm reports negative special items deflated by sales that are higher than the annual cross section mean of non-zero negative special items firms, and zero otherwise.
$DIFF_t$	Lagged reported core earnings and expected current core earnings difference (Informative misclassification signal)	$DIFF_t = CE_{t-1} - E(CE_t)$ where $E(CE_t)$ is the fitted value from the McVay (2006) core earnings model: $CE_t = \varphi_0 + \varphi_1 CE_{t-1} + \varphi_2 ATO_t + \varphi_3 ACC_{t-1} + \varphi_4 ACC_t + \varphi_5 \Delta SALE_t + \varphi_6 NEG\Delta SALE_t + \xi_t$ The core earnings model is estimated out of sample for each industry-year group and excluding firm i CE_t = core earnings = [sales − cost of goods sold − selling, general and administrative expenses #13] / sale #12, ATO_t = assets turnover ratio= [sales #12 /average net operating assets] , where net operating assets = operating assets−operating liabilities = [total assets #6 − cash #1 and short term investments #32] − [total assets #6 − total debt (#9 + #34) − book value of common #60 and preferred equity #130 – minority interest # 38]. I require average net operating assets to be positive, ACC_t = operating accruals = [net income before extraordinary Items #123 − cash from operations (#308 − #124)] / Sales #12, $\Delta SALE_t$ = sale growth = current sale minus lagged sales and divided by current sales, $NEG\Delta SALE_t$ is negative sales growth, equal to percentage change in sales if $\Delta SALE_t < 0$, and zero otherwise.
$SIGMER_t$	Significant merger and acquisitions indicator	Equal to one if annual acquisitions (#129) $>$ 0.2×lagged total assets (#6) , and zero otherwise.

$SIZE_t$	Firm size	Natural logarithm of average total assets.
AR_t	Abnormal returns	The difference between buy-hold returns, minus the buy-hold returns on the CRSP (equally or value) weighted market index over the same period. The return measurement starts four month after the end of the fiscal year from which accounting information is gathered.
$FREQ$	Frequency of negative special items reporting indicator	Equal to one if the firm reported non-zero negative special items in the last year ($FREQ1_t$), over the last three years ($FREQ3_t$), or over the last five years ($FREQ5_t$), and zero otherwise.
$ADJBTM_{t-1}$	Industry adjusted book to market ratio (one year before negative special items)	Book to market ratio minus annual cross section mean of the firm's industry book to market ratio.
$\Delta BTM_{i,t-2\sim t-1}$	Change in book to market ratio (one year before negative special items)	Book to market ratio at $t-1$ minus book to market ratio at $t-2$.
$ADJROA_{t-1}$	Industry adjusted return on assets pre special items(one year before negative special items)	Return on assets pre-special items (earnings before extraordinary items #123 minus special items #17 / average total assets) minus annual cross section mean of the firm's industry return on assets pre-special items.
$\Delta ROA_{i,t-2\sim t-1}$	Change in return on assets pre special items (one year before negative special items)	Return on assets at $t-1$ minus return on assets at $t-2$.
$HI5_t$	Highest negative special items quintile indicator	Equal to one if the firm's negative special items deflated by sales are in the fifth quintile of distribution in the year, and zero otherwise.

$LO1_t$	Lowest negative special items quintile indicator	Equal to one if the firm's negative special items deflated by sales are in the first quintile of distribution in the year, and zero otherwise.
$GAAPCOMPLIANCE_t$	GAAP compliance indicator	Equal to one if the firm's financial statements are not misstated, and zero if the firm financial statements are misstated and subsequently restated (for reasons of accounting restatements and fraud). Data on restating firms are obtained from Audit Analytics and merged with the Compustat-CRSP sample after year 2000.
$MEANSI_t$	Normal negative special items reporting indicator	Equal to one if negative special items deflated by sales are within a ratio of 30% above or below the annual cross section mean of (non-zero) negative special items, and zero otherwise.
SP_t	Reported negative special items	Negative special items as reported by Compustat #17 (deflated by sales). Missing special items and positive special items are set to equal zero.
MCE_t	Misclassified negative core earnings	Measured using a negative special items decomposition approach as described in text.
$MCEind_t$	Misclassified negative core earnings indicator	Equal to one if $MCE \neq 0$, and zero otherwise.
RSP_t	Real negative special items	Measured as the difference between reported negative special items and misclassified negative core earnings.
$RESTATE_t$	Restatement indicator	Equal to one if the firm's fiscal year is misstated and subsequently restated (for reasons of accounting restatements and fraud), and zero otherwise.
ΔREC_t	Change in receivables	Change in receivables #2 divided by average total assets
ΔINV_t	Change in inventory	Change in inventory #3 divided by average total assets
$SFASSETS_t$	Percentage of soft assets	Total assets #6 minus cash #1 and PPE #8 , and divided by average total assets

$\Delta CSALE_t$	Percentage change in cash sale	The difference between current and lagged cash sale and divided by lagged cash sale. Cash sale is measured as sale #12 minus change in receivable #2.
σ_{SALE}	Sales volatility	The standard deviation of the firm's rolling five-year net sales, divided by average total assets. We require at least three non-missing observations.
$ABEMP_t$	Abnormal change in employees	Percentage change in the number of employees #29, divided by percentage change in total assets
LEV_t	Leverage	Long term debt #9 plus short term debt #34, and divided by average total assets.
BV_t	Book value	Total common equity #60 divided by sales.
BTM_t	Book to market ratio	Measured as total common equity #60 divided by market value (#25$\times$stock price from CRSP).
$OIBD_t$	Operating income before special items (Noisy Misclassification signal)	Measured as [sales − cost of goods sold − selling, general and administrative expenses #13] for non-zero negative special items firms.

Tables

Table 1

The Misclassification Decision

The Dichotomous Misclassification Choice Model:

$$\begin{aligned}LARGESP_t = {} & \theta_0 + \theta_1 DIFF_t + \theta_2 SIGMER_t + \theta_3 SIZE_t + \theta_4 AR_t + \theta_5 AR_{t-1} \\ & + \theta_6 FREQ1_t + \theta_7 FREQ2_t + \theta_8 FREQ5_t + \theta_9 ADJBTM_{t-1} \\ & + \theta_{10} \Delta BTM_{t-2\sim t-1} + \theta_{11} ADJROA_{t-1} + \theta_{12} \Delta ROA_{t-2\sim t-1} + \varepsilon_t\end{aligned}$$

Panel A: Descriptive Statistics for Selected Continuous Variables

	The Full Sample				The Negative Special Items Sample			
			Percentile				Percentile	
Variables	**Mean**	**SD**	**(10)**	**(90)**	**Mean**	**SD**	**(10)**	**(90)**
$DIFF_t$	0.006	0.261	−0.098	0.113	0.019	0.181	−0.088	0.147
$SIZE_t$	5.541	2.145	2.864	8.491	6.016	2.090	3.322	8.867
$ADJBTM_{t-1}$	−0.001	0.594	−0.520	0.627	−0.001	0.607	−0.527	0.633
$\Delta BTM_{t-2,t-1}$	0.012	0.474	−0.381	0.416	0.038	0.490	−0.368	0.473
$ADJROA_{t-1}$	−0.652	0.269	−0.988	−0.366	−0.654	0.270	−0.996	−0.369
$\Delta ROA_{t-2,t-1}$	−0.002	0.086	−0.082	0.074	−0.005	0.086	−0.087	0.068

Panel B: Logistic Regression and Ordinary Least Square Coefficients Results for Dichotomous Misclassification Choice Models

Variables	Predicted Sign Model (1)&(2)	Model (1) Dependent Variable $LARGESP_t$ LOGIT	Model (1) OLS-LPM	Model (2) Dependent Variable $HI5_t$ LOGIT	Model (2) OLS-LPM	Predicted Sign Model (3)	Model (3) Dependent Variable $LO1_t$ LOGIT	Model (3) OLS-LPM
Intercept	±	−1.152***	0.246***	−1.362***	0.212***	±	−1.809***	0.135***
		(−13.68)	(19.61)	(−15.46)	(17.73)		(−22.18)	(10.26)
$DIFF_t$	+	2.274***	0.380***	2.232***	0.355***	−	−1.049***	−0.148***
		(11.99)	(13.49)	(11.62)	(12.65)		(−9.54)	(−10.45)
$SIGMER_t$	+	0.478***	0.070***	0.567***	0.079***	−	−0.328***	−0.053***
		(5.61)	(4.91)	(6.55)	(5.62)		(−3.59)	(−3.98)
$SIZE_t$	−	−0.156***	−0.024***	−0.150***	−0.021***	+	0.126***	0.021***
		(−13.97)	(−15.81)	(−12.87)	(−14.60)		(13.34)	(12.84)
AR_t	−	−0.405***	−0.058***	−0.389***	−0.051***	+	0.254***	0.042***
		(−8.57)	(−10.01)	(−7.88)	(−9.19)		(8.73)	(8.16)
AR_{t-1}	−	−0.334***	−0.043***	−0.351***	−0.041***	+	0.191***	0.033***
		(−6.84)	(−7.59)	(−6.60)	(−7.40)		(6.46)	(6.22)
$FREQ1_t$	+	0.186***	0.028***	0.201***	0.028***	−	−0.161**	−0.027**
		(3.45)	(3.59)	(3.55)	(3.68)		(−3.16)	(−3.14)
$FREQ2_t$	+	0.178**	0.026**	0.216***	0.030**	−	−0.160**	−0.026**
		(2.93)	(2.79)	(3.42)	(3.28)		(−2.66)	(−2.73)
$FREQ5_t$	+	0.150*	0.020**	0.188*	0.023*	−	−0.328***	−0.051***
		(2.05)	(2.79)	(2.50)	(2.12)		(−4.28)	(−4.64)
$ADJBTM_{t-1}$	+	0.134***	0.023***	0.147***	0.022***	−	−0.056	−0.008
		(3.49)	(3.69)	(3.66)	(3.77)		(−1.44)	(−1.34)
$\Delta BTM_{t-2\sim t-1}$	+	0.042	0.008	0.004	0.002	−	-0.0833	−0.014
		(0.81)	(1.02)	(0.08)	(0.25)		(-1.79)	(−1.79)
$ADJROA_{t-1}$	−	−0.447***	−0.080***	−0.424***	−0.072***	+	0.010	0.011
		(−5.77)	(−6.75)	(−5.23)	(−6.26)		(1.31)	(0.87)
$\Delta ROA_{t-2\sim t-1}$	−	−1.102***	−0.202***	−0.942**	−0.165***	+	0.800***	0.111***
		(−3.98)	(−4.55)	(−3.24)	(−3.81)		(3.59)	(3.33)
Pseudo R2		6.7%		6.6%			2.7%	
R2			6.8%		6.3%			2.7%
Sample size		16,029	16,029	16,029	16,029		16,029	16,029

Panel C: Marginal Effects and Changes in Probabilities of the Misclassification Decision

Variables	Model (1) MEM (AV)	Model (1) MEM (SV)	Model (1) ΔPr $(Q5-Q1)$ Other variables at mean	Model (2) MEM (AV)	Model (2) MEM (SV)	Model (2) ΔPr $(Q5-Q1)$ Other variables at mean	Model (3) MEM (AV)	Model (3) MEM (SV)	Model (3) ΔPr $(Q5-Q1)$ Other variables at mean
$DIFF_t$	0.332	0.042	16.5%	0.293	0.037	14.5%	−0.172	−0.028	11.2%
$SIGMER_t$	0.070	0.082	9.7%	0.074	0.086	10.5%	−0.054	−0.068	6%
$SIZE_t$	−0.023	−0.029	12.1%	−0.020	−0.027	11.3%	0.021	0.031	12.1%
AR_t	−0.059	−0.034	13.6%	−0.051	−0.029	11.7%	0.042	0.025	10.3%
AR_{t-1}	−0.049	−0.032	12.7%	−0.046	−0.030	11.7%	0.031	0.025	10.1%
$FREQ1_t$	0.027	0.024	2.4%	0.026	0.023	2.3%	−0.026	−0.024	2.4%
$FREQ2_t$	0.026	0.019	1.9%	0.028	0.023	2.3%	−0.026	−0.023	2.2%
$FREQ5_t$	0.022	0.016	1.7%	0.024	0.021	2.1%	−0.054	−0.052	4.8%
$ADJBTM_{t-1}$	0.019	0.003	1.3%	0.019	0.003	1.2%	−0.009	−0.001	0.6%
$\Delta BTM_{t-2\sim t-1}$	0.006	−0.004	1.5%	0.001	−0.002	0.9 %	−0.014	−0.000	0.1%
$ADJROA_{t-1}$	−0.065	−0.015	6%	−0.056	−0.014	5.7%	0.016	0.003	01.1%
$\Delta ROA_{t-2\sim t-1}$	−0.161	−0.006	2.5%	−0.124	−0.005	2%	0.131	0.008	3%
(I): $\Pr(Y=1)$ at lower(upper) Q for variables with positive (negative) coefficients			1.5 %			1.3%			2.4%
(II) $\Pr(Y=1)$ at upper (lower) Q for variables with negative (positive) coefficients			82.4%			82.3%			58.3%
ΔPr (II−I)			80.9%			81.1%			56%

Panel A shows the distribution of selected variables. SD is the standard deviation.
Panel B shows the regression results for the negative special items sample. The LOGIT column reports the logistic regression coefficients. The OLS-LPM reports the ordinary least squares linear probability model coefficients.
In Panel C, MEM (AV) is the marginal effect at means based on actual variables. MEM (SV) is the marginal effect at means based on standardized variables (variables are ranked into five quintiles). Indicator variables take the value of 1 or 0 in both actual and standardized variables regressions.
In both probabilities (I) and (II), an indicator variable is zero (one) when the variable has a positive (negative) coefficient in the logistic model.
t-statistics are calculated using robust standard errors. All variables are defined in the Appendix. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 2

The Misclassification Decision Compliance with Accounting Standards

Panel A: Logistic Regression Results for the Dichotomous Misclassification Choice Model that Incorporates GAAP Compliance:

$$HI5_t = \eta_0 + \eta_1 GAAPCOMPLIANCE_t + \eta_2 DIFF_t + \gamma CONTROLS$$

Dependent Variable: $HI5_t$		
Variables	**Coefficients**	
$GAAPCOMPLIANCE$	−0.264*** (−3.16)	−0.187** (−2.35)
$DIFF_t$	2.398*** (10.58)	2.179*** (9.64)
Controls Included	Yes	Yes
Year and Industry Effects	Yes	No
Pseudo R^2	13.2%	7%
Sample size	12,184	12,291
GAAP Compliance Firm-Year	35,016	35,016
Non-GAAP Compliance Firm-Year	3,266	3,266

Panel B: Logistic Regression Results for a Normal Reporting Strategy of Negative Special Items:

$$MEANSI_t = \eta_0 + \eta_1 GAAPCOMPLIANCE_t + \eta_2 DIFF_t + \gamma CONTROLS$$

Dependent Variable: $MEANSI_t$		
Variables	**Coefficients**	
$GAAPCOMPLIANCE$	−0.095 (−0.92)	−0.055 (−0.54)
$DIFF_t$	−0.046 (−0.25)	−0.086 (−0.41)
Controls Included	Yes	Yes
Year and Industry Effects	Yes	No
Pseudo R^2	2.9%	0.9%
Sample Size	12,215	12,291

The sample period is 2000-2014 from the merge of Audit Analytics with the Compustat-CRSP sample after 2000. Regressions are estimated for non-zero negative special items. Coefficients are measured using logistic regressions. *t*-statistics are calculated using robust standard errors. All variables are defined in the Appendix. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. *CONTROLS* (results suppressed) are the same set of control variables used in Table 1.

Table 3

Restatements and Fraud Association with Negative Special Items Components

The Restatement Model:

$$\begin{aligned} RESTATE_t = {} & \kappa_0 + \kappa_1 SP_t + \kappa_2 \Delta REC_t + \kappa_3 \Delta INV_t + \kappa_4 SFASSET_t + \kappa_5 \Delta CSALE_t \\ & + \kappa_6 \sigma_{SALE} + \kappa_7 ABEMP_t + \kappa_8 \Delta ROA_t + \kappa_9 AR_t + \kappa_{10} AR_{t-1} \\ & + \kappa_{11} BTM_t + \kappa_{12} LEV_t + \zeta_t \end{aligned}$$

Panel A: Descriptive Statistics for Selected Variables

	The Full Restatement Sample (2000-2014)			
			Percentile	
Variables	**Mean**	**SD**	**(10)**	**(90)**
SP_t	−0.034	0.108	−0.073	0
MCE_t	−0.003	0.011	−0.006	0
RSP_t	−0.031	0.102	−0.063	0
ΔREC_t	0.008	0.060	−0.047	0.067
ΔINV_t	0.005	0.044	−0.028	0.046
$SFASSET_t$	0.559	0.250	0.194	0.890
$\Delta CSALE_t$	0.103	0.379	−0.225	0.441
σ_{SALE}	0.160	0.154	0.029	0.344
$ABEMP_t$	−0.045	0.272	−0.287	0.202
ΔROA_t	−0.004	0.090	−0.087	0.073
BTM_t	0.713	0.719	0.158	1.461
LEV_t	0.226	0.220	0	0.532

Panel B: Ordinary Least Square Logistic Regression Results for the Restatement Model

Variables	Negative Special Items		Negative Special Items Decomposition		Misclassification Indicator	
	OLS-LPM	**LOGIT (MEM)**	**OLS-LPM**	**LOGIT (MEM)**	**OLS-LPM**	**LOGIT (MEM)**
Intercept	0.120*** (4.95)		0.117*** (4.75)		0.118*** (4.86)	
SP_t	0.061*** (2.64)	0.057*** (2.95)				
MCE_t			0.492** (2.15)	0.411** (2.26)		
RSP_t			0.029 (1.07)	0.029 (1.15)		
$MCEind_t$					0.014*** (3.17)	0.013*** (3.25)
ΔREC_t	0.008 (0.24)	0.010 (0.28)	0.010 (0.28)	0.010 (0.30)	0.007 (0.19)	0.007 (0.20)
ΔINV_t	0.088** (1.99)	0.085** (1.99)	0.089** (2.01)	0.086** (2.00)	0.089** (2.01)	0.086** (2.01)
$SFASSET_t$	0.018* (1.78)	0.017* (1.77)	0.018* (1.75)	0.017* (1.74)	0.015 (1.52)	0.015 (1.51)
$\Delta CSALE_t$	0.003 (0.52)	0.003 (0.53)	0.003 (0.54)	0.003 (0.55)	0.003 (0.47)	0.003 (0.48)
σ_{SALE}	−0.010 (−0.78)	−0.011 (−0.83)	−0.010 (−0.77)	−0.011 (−0.82)	−0.009 (−0.67)	−0.009 (−0.71)
$ABEMB$	−0.012 (−1.47)	−0.011 (−1.46)	−0.012 (−1.44)	−0.011 (−1.42)	−0.011 (−1.32)	−0.010 (−1.28)
ROA_t	−0.004 (−0.19)	−0.003 (−0.15)	−0.005 (−0.20)	−0.004 (−0.16)	−0.006 (−0.26)	−0.005 (−0.23)
AR_t	0.002 (0.62)	0.001 (0.65)	0.001 (0.59)	0.001 (0.62)	0.001 (0.51)	0.001 (0.54)
AR_{t-1}	0.001 (0.53)	0.001 (0.54)	0.001 (0.53)	0.001 (0.54)	0.001 (0.41)	0.001 (0.42)
BTM_t	−0.008*** (−2.92)	−0.009*** (−2.84)	−0.008*** (−2.90)	−0.009*** (−2.82)	−0.008*** (−2.79)	−0.008*** (−2.72)
LEV_t	0.027*** (2.57)	0.026*** (2.63)	0.026*** (2.52)	0.025** (2.57)	0.027** (2.54)	0.025*** (2.59)
(Pseudo) R^2	1%	2%	1%	2%	1%	2%
Sample Size	23,053	22,971	23,053	22,971	23,053	22,971

The OLS-LPM column reports coefficients based on ordinary least square linear probability model. LOGIT (MEM) reports the logistic regression marginal significance. Industry fixed effects are included, and results are consistent without industry fixed effects. The sample period is 2000-2014. *t*-statistics are calculated using robust standard errors. All variables are defined in the Appendix. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 4

Misclassified Negative Core Earnings Forecast Properties

The Earnings Forecast Model:

No Decomposition: $E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega_{2,3}^{*} SP_t + \omega_4 BV_t + error_{t+\tau}$

Decomposition: $E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega_2 MCE_t + \omega_3 RSP_t + \omega_4 BV_t + error_{t+\tau}$

Panel A: Descriptive Statistics for Selected Variables

	The Full Sample				**The Negative Special Items Sample**			
			Percentile				**Percentile**	
Variables	**Mean**	**SD**	**(10)**	**(90)**	**Mean**	**SD**	**(10)**	**(90)**
AE_t	−0.156	0.480	−0.401	0.054	−0.224	0.542	−0.580	0.0365
EBE_t	−0.079	0.492	−0.298	0.152	−0.160	0.567	−0.515	0.119
$EBESP_t$	−0.049	0.423	−0.222	0.157	−0.075	0.447	−0.304	0.151
CE_t	0.0698	0.383	−0.114	0.347	0.043	0.392	−0.172	0.316
SP_t	−0.030	0.099	−0.065	0	−0.075	0.145	−0.203	−0.002
MCE_t	−0.003	0.012	−0.005	0	−0.007	0.017	−0.021	0
Non-zero MCE_t	−0.013	0.021	−0.040	−0.0002	−0.013	0.021	−0.040	−0.0002
RSP_t	−0.030	0.093	−0.056	0	−0.068	0.137	−0.182	0.001
Non-zero GSP_t	−0.070	0.138	−0.188	−0.002	−0.070	0.138	−0.188	−0.002
BV_t	0.842	1.148	−0.127	1.733	0.788	1.077	−0.093	1.652

Panel B: Earnings Forecast for the Full Sample with No Decomposition for Negative Special Items

Dependent variable $E_{t+\tau}$	**Forecast Horizon** $(t+\tau)$	**Forecasting Coefficients** ω_0	ω_1	$\omega^*_{2,3}$	ω_4	**Adj.** R^2	**Obs.**
Abnormal Earning $AE_{t+\tau}$	1	−0.059*** (−22.49)	0.726*** (74.36)	0.401*** (12.62)	−0.179*** (-69.12)	0.62	56,328
	2	−0.058*** (−18.17)	0.587*** (45.36)	0.181*** (4.80)	−0.162*** (−48.58)	0.45	46,929
	3	−0.053*** (−14.93)	0.482*** (31.70)	0.107* (2.34)	−0.149*** (−37.90)	0.36	39,161
Earnings $EBE_{t+\tau}$	1	−0.058*** (−21.09)	0.782*** (68.92)	0.427*** (12.06)	−0.070*** (−22.98)	0.50	56,328
	2	−0.048*** (−15.03)	0.656*** (46.91)	0.176*** (4.49)	−0.069*** (−19.61)	0.37	46,978
	3	−0.036*** (−10.11)	0.553*** (35.00)	0.104* (2.26)	−0.0658*** (−16.46)	0.28	39,337
Earnings before Special Items $EBESP_{t+\tau}$	1	−0.047*** (−20.59)	0.737*** (76.37)	0.192*** (7.14)	−0.054*** (−21.43)	0.55	56,328
	2	−0.035*** (−12.91)	0.615*** (51.20)	0.081* (2.44)	−0.054*** (−18.00)	0.40	46,978
	3	−0.023*** (−7.51)	0.517*** (37.73)	−0.008 (−0.22)	−0.052*** (−15.26)	0.30	39,337

Panel C: Earnings Forecast for the Full Sample with Decomposition for Negative Special Items

Dependent variable $e_{t+\tau}$	**Forecast Horizon** $(t+\tau)$	**Forecasting Coefficients** ω_0	ω_1	**Special Items Components** ω_2	ω_3	ω_4	**Adj.** R^2	**Obs.**
Abnormal Earnings $AE_{t+\tau}$	1	−0.059*** (−22.41)	0.727*** (74.34)	0.761** (3.07)	0.374*** (9.78)	−0.179*** −69.13	0.62	56,328
	2	−0.057*** (−17.99)	0.588*** (45.44)	1.199*** (4.11)	0.105* (2.33)	−0.162*** (−48.60)	0.45	46,929
	3	−0.053*** (−14.77)	0.483*** (31.76)	1.168*** (3.38)	0.026 (0.50)	−0.149*** (−37.91)	0.36	39,161
Earnings $EBE_{t+\tau}$	1	-0.058*** (-21.06)	0.782*** (68.93)	0.737** (2.72)	0.403*** (9.34)	-0.0695*** (-22.98)	0.50	56,328
	2	−0.047*** (−14.90)	0.656*** (46.96)	0.918** (3.07)	0.120* (2.56)	−0.069*** (−19.60)	0.37	46,978
	3	−0.035*** (−9.99)	0.553*** (35.02)	0.873* (2.48)	0.0455 (0.86)	−0.066*** (−16.45)	0.28	39,337

Table 4 Panel C (continued)

Earnings before Special Items	1	−0.047***	0.737***	0.861***	0.142***	−0.052***	0.55	56,328
		(−20.42)	(76.44)	(4.06)	(4.35)	(−21.44)		
$EBESP_{t+\tau}$	2	−0.034***	0.616***	0.827**	0.0248	-0.054***	0.40	46,978
		(−12.75)	(51.26)	(3.27)	(0.62)	(-17.99)		
	3	−0.022***	0.517***	0.694*	−0.0615	−0.052***	0.30	39,337
		(−7.39)	(37.75)	(2.38)	(−1.38)	(−15.26)		

Panel D: Earnings before Special Items Forecast for Special Items Firms Subsamples

The Subsample	Forecast Horizon $(t+\tau)$	Forecasting Coefficients					Adj. R^2	Obs.
				Special Items Components				
		ω_0	ω_1	ω_2	ω_3	ω_4		
Negative Special Items Subsample	1	−0.033***	0.711***	0.952***	0.185***	−0.057***	54%	21,514
		(−7.93)	(44.88)	(4.42)	(5.63)	(-11.79)		
	2	−0.019***	0.573***	0.961***	0.103**	−0.051***	39%	17,282
		(-4.06)	(28.65)	(3.73)	(2.58)	(−9.59)		
	3	−0.007	0.453***	0.791**	0.026	−0.052***	28%	13,979
		(−1.27)	(19.93)	(2.66)	(0.59)	(−8.38)		
Misclassified Negative Core Earnings Subsample	1	−0.028***	0.743***	1.059***	0.126**	-0.064***	58%	12,192
		(−4.95)	(38.65)	(4.45)	(2.86)	(-10.80)		
	2	−0.019**	0.615***	0.980***	0.0646	-0.0539***	42%	9,918
		(-2.99)	(24.40)	(3.38)	(1.13)	(−7.59)		
	3	0.001	0.468***	0.984**	0.008	-0.052***	30%	7,956
		(0.10)	(16.34)	(2.93)	(0.13)	(-6.50)		

The table provides results of pooled OLS regressions of earnings forecast models that include core earnings and special items. The earnings forecast model is estimated using reported negative special items (no-decomposition) and the two fundamental compositions of negative special items (decomposition). Regressions are estimated using the full sample, in addition to reduced subsamples as indicated in the table. *t*-statistics are calculated using robust standard errors. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 5

The Market Perception of Misclassified Negative Core Earnings

The Pricing Model

No Decomposition: $AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha^*_{2,3} \Delta SP_t + \alpha_4 \Delta BV_t + error_t$

Decomposition: $AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha_2 \Delta MCE_t + \alpha_3 \Delta RSP_t + \alpha_4 \Delta BV_t + error_t$

Panel A: Pricing Model for the Full Sample with No Decomposition for Negative Special Items

	Pricing Coefficients					
Dependent Variable	α_0	α_1	$\alpha^*_{2,3}$	α_4	**Adj. R^2**	**Obs.**
Abnormal Returns	0.040*** (10.27)	0.663*** (15.49)	0.462*** (8.78)	0.121*** (10.09)	3%	56,328

Panel B: Pricing Model for the Full Sample with Decomposition for Negative Special Items

	Pricing Coefficients						
Dependent Variable			Special Items Components			**Adj. R^2**	**Obs.**
	α_0	α_1	α_2	α_3	α_4		
Abnormal Returns	0.040*** (10.27)	0.663*** (15.48)	0.464 (1.37)	0.462*** (8.08)	0.121*** (10.09)	3%	

Panel C: Pricing of Earnings Components for Special Items Firms Subsamples

The Subsample	Pricing Coefficients					Adj. R^2	Obs.
			Special Items Components				
	α_0	α_1	α_2	α_3	α_4		
Firms Reporting Negative Special Items in Years t and $t-1$	0.0289** (3.04)	0.673*** (9.75)	0.198 (0.36)	0.447*** (4.45)	0.159*** (6.71)	3%	12,451
Firms Reporting Negative Special Items in Years t and $t-1$ that have Misclassified at least Once in those Two years.	0.0338*** (3.37)	0.680*** (9.76)	0.186 (0.34)	0.457*** (4.24)	0.156*** (6.40)	3%	11,015
Firms Reporting Negative Special Items in Years t and $t-1$ that have Misclassified in Both Years	0.0553*** (3.41)	0.654*** (6.99)	0.365 (0.44)	0.568*** (4.40)	0.149*** (4.83)	3%	5,318

The table provides results of pooled OLS regressions of abnormal returns on changes in earnings components that include core earnings and special items. The pricing model is estimated using reported negative special items (no-decomposition) and the two fundamental compositions of negative special items (decomposition). Regressions are estimated using the full sample, in addition to reduced subsamples as indicated in the table. AR_t is equally weighted abnormal returns. The return cumulation period begins four months after the end of the fiscal year. *t*-statistics are calculated using robust standard errors. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6

The *Shorrocks-Shapley* Decomposed R^2 and Economic Significance of Negative Special Items Forecastability for Portfolio Assignment Based on the Informative Misclassification Signal

Panel A: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Abnormal Earnings

	Earnings Forecast: Abnormal Earnings		
Informative Signal Portfolio	**Total adjusted R^2 from the Earnings forecast regression**	***Shorrocks-Shapely* Decomposition of Adjusted R^2**	**Economic Significance in Basis Points**
Lowest- *DIFF*	64%	3.71%	168
Highest- *DIFF*	57%	7.30%	526

Panel B: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Earnings

	Earnings Forecast: Earnings		
Informative Signal Portfolio	**Total adjusted R^2 from the Earnings Forecast Regression**	***Shorrocks-Shapely* Decomposition of Adjusted R^2**	**Economic Significance in Basis Points**
Lowest- *DIFF*	53%	4.28%	179
Highest- *DIFF*	46%	9.74%	566

Panel C: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Earnings Before Special Items

	Earnings Forecast: Earnings Before Special Items		
Informative Signal Portfolio	**Total adjusted R^2 from the Earnings Forecast Regression**	**Shorrocks-Shapely Decomposition of Adjusted R^2**	**Economic Significance in Basis Points**
Lowest- *DIFF*	58%	3.30%	47
Highest- *DIFF*	50%	6.55%	295

Economic Significance in basis points is the product of the negative special items coefficient estimate from an OLS portfolio regression of one-year ahead of the earnings metric on core earnings, negative special items and book value, and the standard deviation of negative special items in the portfolio sample. It shows the impact of one standard deviation change on the next year earnings metric. The *Shorrocks-Shapley* decomposition of adjusted R^2 shows the *contribution* of negative special items to the total adjusted R^2 of the portfolio regression. The R^2 decomposition approach provides an additive decomposition of the estimated adjusted R^2, and shows the relative contribution of each independent variable to the total adjusted R^2. The tables show only the negative special items *Shorrocks-Shapley* values. Lowest (Highest) - *DIFF* portfolio corresponds to portfolios 1 and 2 (4 and 5). Portfolio formation is based on ranking firms into five portfolios each year with respect to the *DIFF* value (rebalanced).

Table 7

The *Shorrocks-Shapley* Decomposed R^2 and Economic Significance of Negative Special Items Forecastability for Portfolio Assignment Based on the Noisy Misclassification Signal

Panel A: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Abnormal Earnings

Noisy Signal Portfolio	Earnings Forecast: Abnormal Earnings		
	Total adjusted R^2 from the Earnings Forecast Regression	*Shorrocks-Shapely* Decomposition of Adjusted R^2	Economic Significance in Basis Points
Lowest-*OIBD*	62%	12.44%	726
Highest-*OIBD*	20%	12.64%	299

Panel B: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Earnings

Noisy Signal Portfolio	Earnings Forecast: Earnings		
	Total adjusted R^2 from the Earnings Forecast Regression	*Shorrocks-Shapely* Decomposition of Adjusted R^2	Economic Significance in Basis Points
Lowest-*OIBD*	51%	14.64%	798
Highest-*OIBD*	5%	35.61%	300

Panel C: *Shorrocks-Shapley* R^2 Decomposition and Economic Significance of Negative Special Items with Respect to One-Year Ahead Earnings Before Special Items

Noisy Signal Portfolio	Earnings Forecast: Earnings Before Special Items		
	Total Adjusted R^2 from the Earnings Forecast Regression	*Shorrocks-Shapely* Decomposition of Adjusted R^2	Economic Significance in Basis Points
Lowest-*OIBD*	56%	11.67%	399
Highest-*OIBD*	6%	7.14%	116

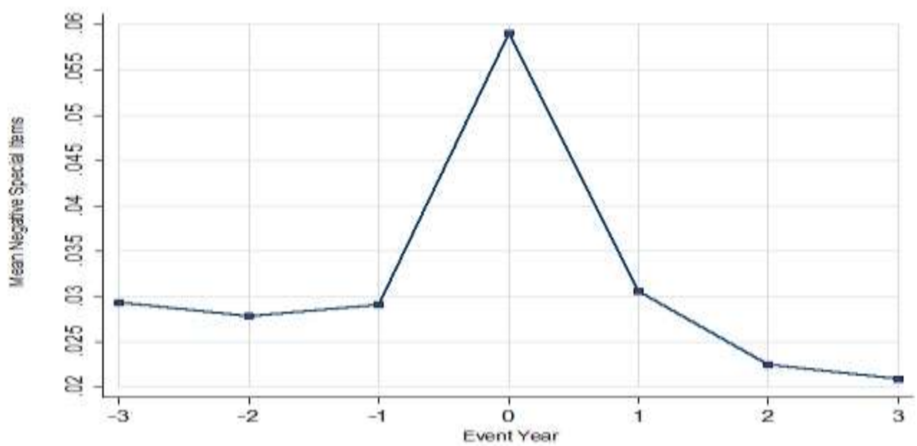
Economic Significance in basis points is the product of the negative special items coefficient estimate from a portfolio (OLS) regression of one-year ahead of the earnings metric on core earnings, negative special items and book value; and the standard deviation of negative special items in the portfolio sample. It shows the impact of one standard deviation change on the next year's earnings metric. The *Shorrocks-Shapley* decomposition of adjusted R^2 shows the *contribution* of negative special items to the total adjusted R^2 from the portfolio regression. The decomposition approach provides an additive decomposition of the estimated adjusted R^2, and shows the relative contribution of each independent variable to the total adjusted R^2. The table shows only the negative special items' *Shorrocks-Shapley* values. Lowest (Highest) - *OIBD* portfolio corresponds to portfolios 1 and 2 (4 and 5). Portfolio formation is based on ranking firms into five portfolios each year with respect to the *OIBD* value (rebalanced).

Figures

Figure 1

Inter-Temporal Analysis of Means of Negative Special Items Surrounding Positive and Negative Deviations of Prior Year's Reported Core Earnings and Current Year's Predicted Core Earnings as Measured by *DIFF*

Panel A: Times Series Properties (Seven-Years Window) of Negative Special Items Deflated by Sales Surrounding the Event Year of Positive *DIFF*



Panel B: Times Series Properties (Seven-Year Window) of Negative Special Items Deflated by Sales Surrounding the Event Year of Negative *DIFF*

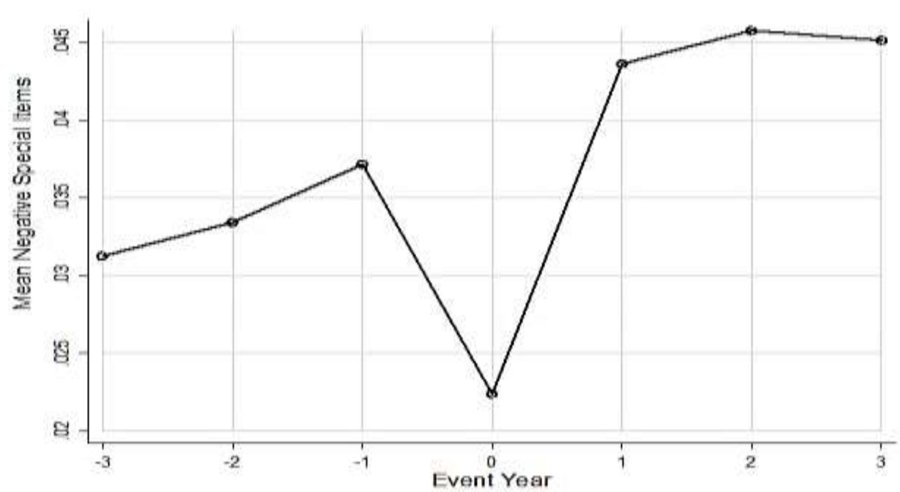
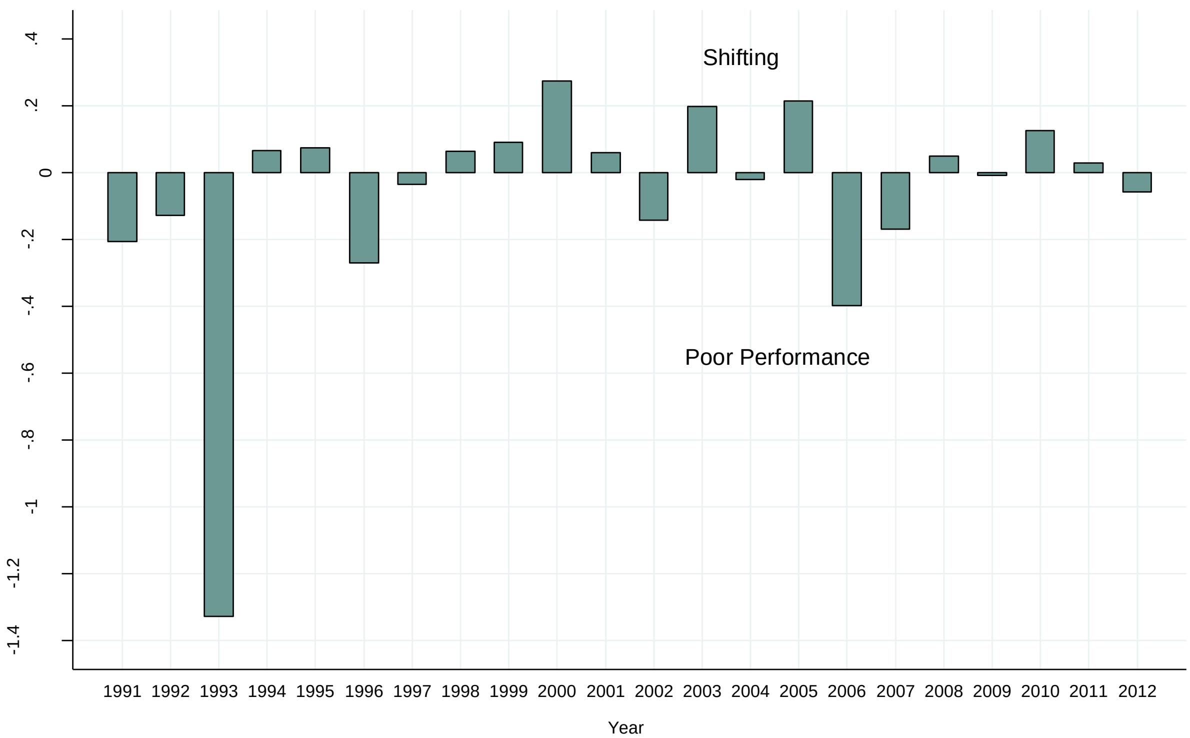


Figure 2

Negative Special Items' Association with Contemporaneous Unexpected Core Earnings

The Model: $CE_t - E\left(CE_t\right) = a_0 + a_1\ SP_t + error_t$



The y-axis represents the mean coefficient of negative special items from contemporaneous industry-year regressions of unexpected core earnings on negative special items. Unexpected core earnings are the difference between reported core earnings and expected core earnings. Core earnings expectations are estimated out-of-sample using McVay's (2006) model of core earnings:

$$CE_t = \varphi_0 + \varphi_1 CE_{t-1} + \varphi_2 ATO_t + \varphi_3 ACC_{t-1} + \varphi_4 ACC_t + \varphi_5 \Delta SALE_t + \varphi_6 NEG\Delta SALE_t + \xi_t$$

Negative special items are measured in absolute terms in this regression. Positive coefficients on negative special items are consistent with shifting negative core earnings to negative special items. Negative coefficients on negative special items are consistent with poor performance rather than misclassification and shifting. All variables are defined in the Appendix.

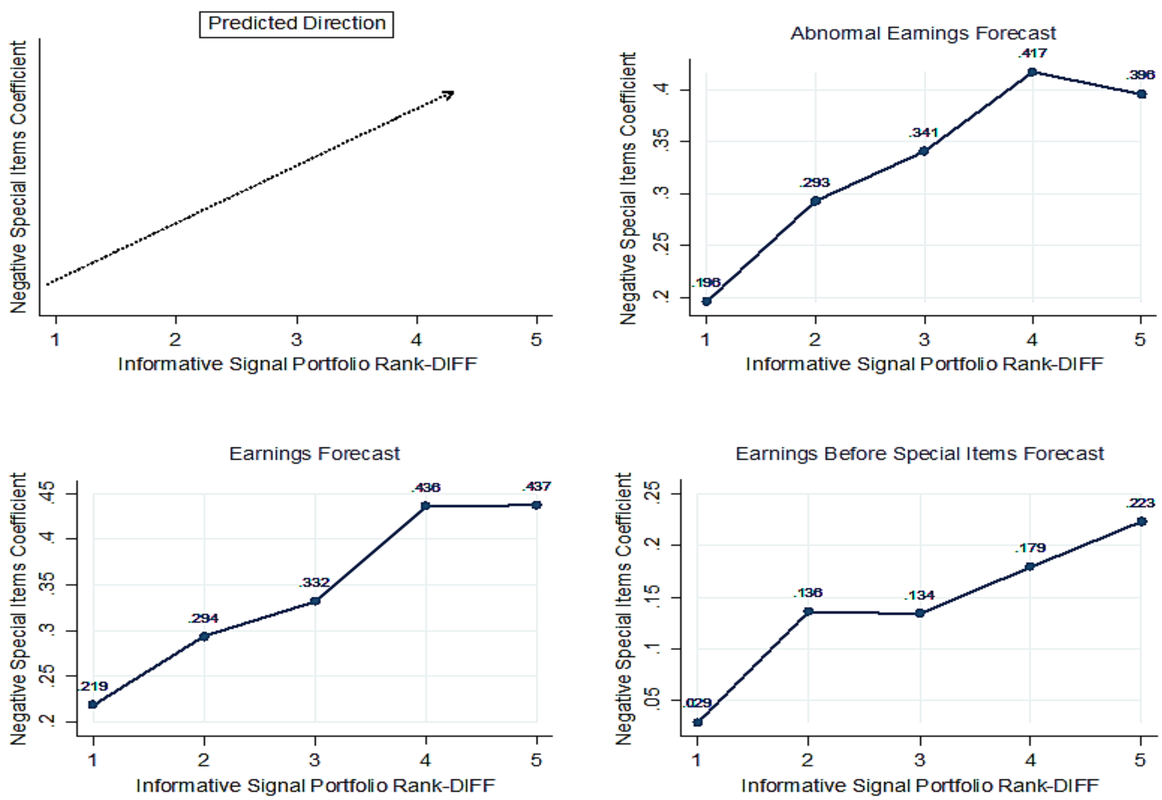
Figure 3

Changes in the Forecast Information Content of Reported Negative Special Items Across Portfolios Formed on the Informative Misclassification Signal

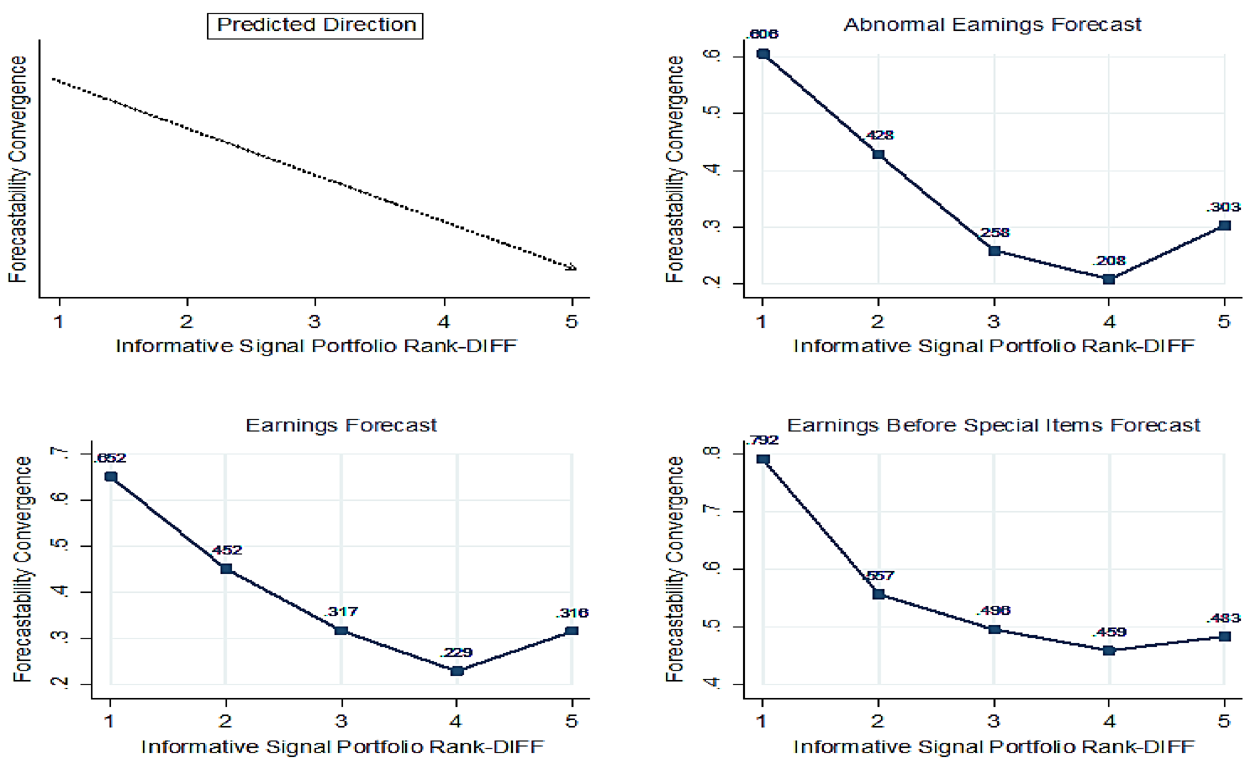
The Forecast Model

$$E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega_{2,3}^{*} SP_t + \omega_4 BV_t + error_{t+\tau}$$

Panel A: Negative Special Items Coefficient Estimates ($\omega_{2,3}^{*}$) with Respect to on One-Year Ahead Earnings Across the Informative Misclassification Signal



Panel B: Negative Special Items Forecastability Convergence with Core Earnings $(\omega_1 - \omega^*_{2,3})$ with Respect to One-Year Ahead Earnings Across the Informative Misclassification Signal



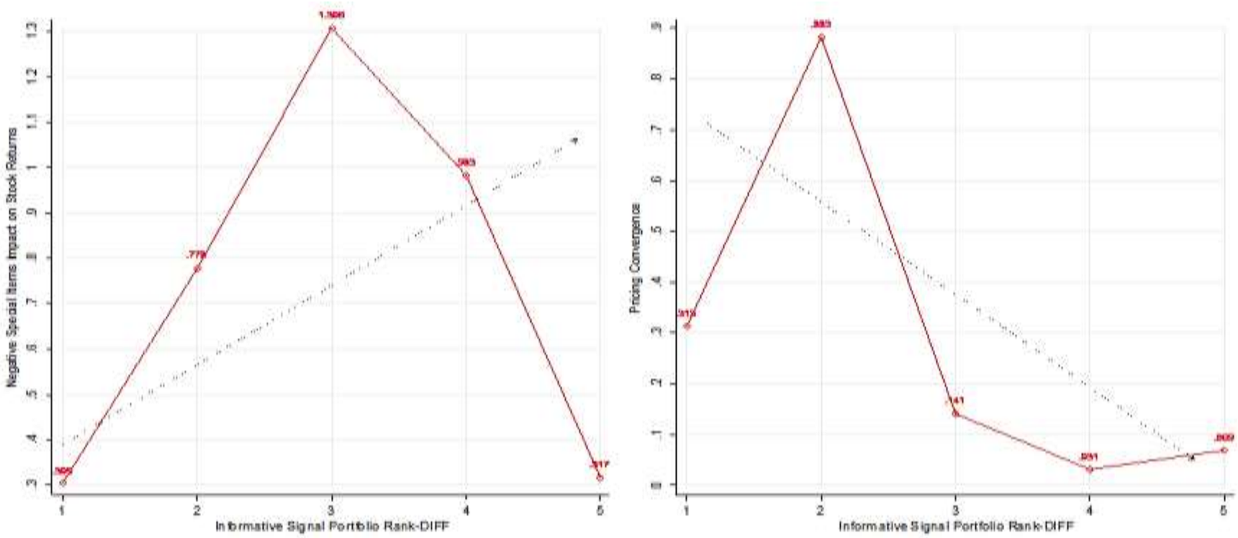
The figure shows the change in the forecasting ability of negative special items over portfolios formed on the Informative misclassification signal. The forecast model is estimated per portfolio using OLS. The dependent earnings forecast variable is: abnormal earnings, earnings, and earnings before special items. Portfolios are formed annually based on the *DIFF* signal. The x-axis represents the portfolio rank. In Panel A, the y-axis represents $\omega^*_{2,3}$ estimates in each portfolio. In Panel B, the y-axis represents forecastability convergence measured as $(\omega_1 - \omega^*_{2,3})$. The earnings metrics and all definitions of other variables are provided in the Appendix.

Figure 4

Stock Return Association with Negative Special Items Conditional on the Informative Misclassification Signal

The Pricing Model

$$AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha^*_{2,3} \Delta SP_t + \alpha_4 \Delta BV_t + error_t$$



The figure shows the stock return association with negative special items over portfolios formed on the Informative misclassification signal. The pricing model is estimated per portfolio using OLS. Portfolios are formed annually based on the *DIFF* signal. The x-axis represents the portfolio rank. The y-axis represents either $\alpha^*_{2,3}$ estimates in each portfolio or pricing convergence measured as ($\alpha_1 - \alpha^*_{2,3}$). AR_t is value weighted abnormal returns. All definitions of variables are provided in the Appendix.

Figure 5

Changes in the Forecast Information Content of Reported Negative Special Items across Portfolios Formed on the Reporting (Noisy) Misclassification Signal

The Forecast Model

$$E_{t+\tau} = \omega_0 + \omega_1 CE_t + \omega^*_{2,3} SP_t + \omega_4 BV_t + error_{t+\tau}$$

Panel A: Negative Special Items Coefficient Estimates ($\omega^*_{2,3}$) with Respect to on One-Year Ahead Earnings Across the Reporting (Noisy) Misclassification Signal

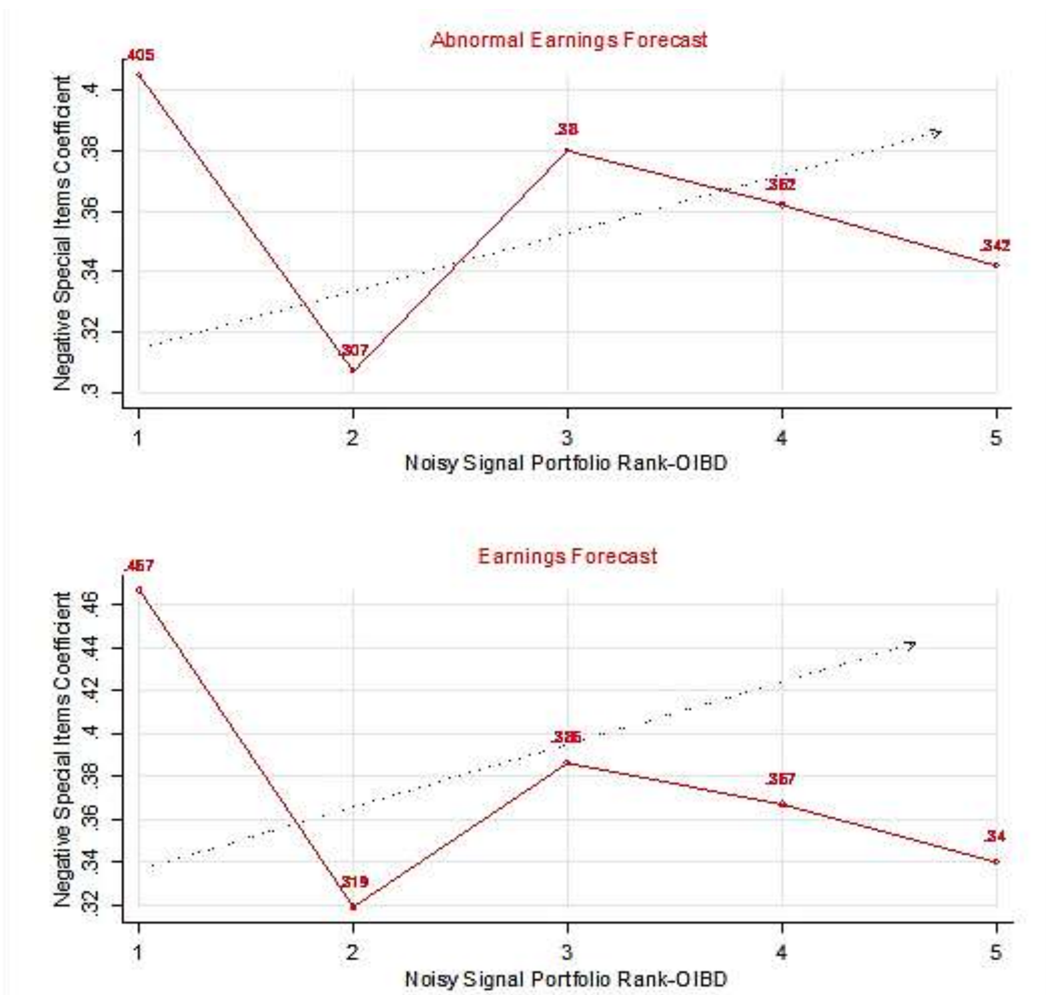


Figure 5 Panel A (Continued)

Panel B: Negative Special Items Forecastability Convergence with Core Earnings $(\omega_1 - \omega^*_{2,3})$ with Respect to One-Year Ahead Earnings Across the Reporting (Noisy) Misclassification Signal

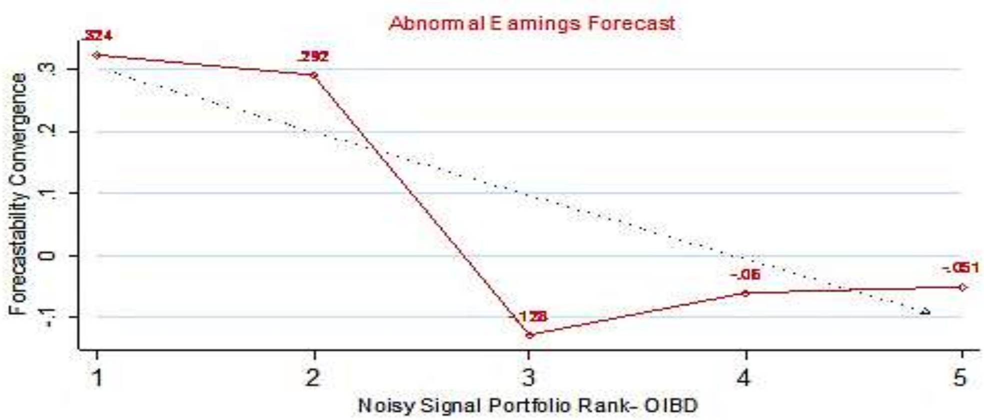


Figure 5 Panel B (Continued)

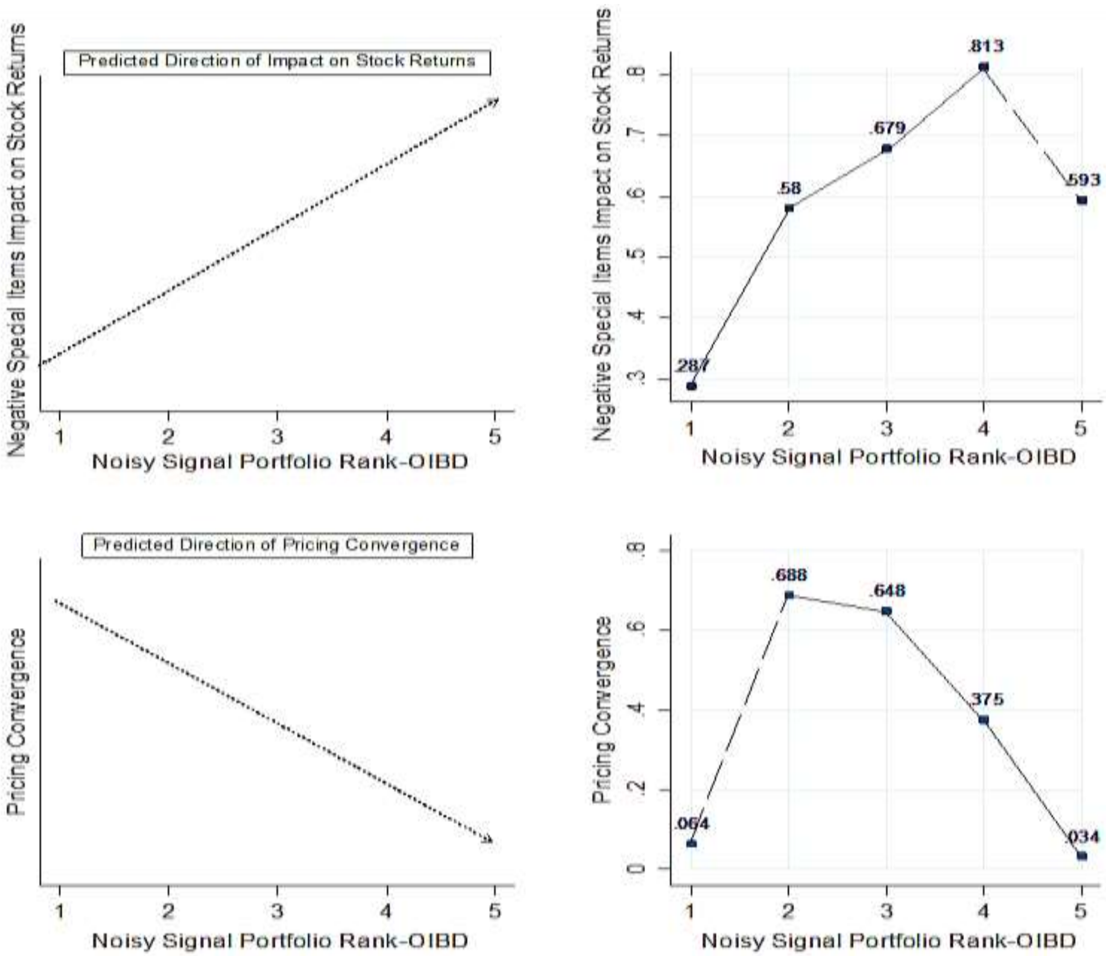
The figure shows the change in the forecasting ability of negative special items over portfolios formed on the informative misclassification signal. The forecast model is estimated per portfolio using OLS. The dependent earnings forecast variable is: abnormal earnings, earnings, and earnings before special items. Portfolios are formed annually based on $OIBD_t$. The x-axis represents the portfolio rank. In Panel A, the y-axis represents $\omega^*_{2,3}$ estimates in each portfolio. In Panel B, the y-axis represents forecastability convergence measured as ($\omega_1 - \omega^*_{2,3}$). The earnings metrics and all definitions of other variables are provided in the appendix.

Figure 6

Stock Return Association to Negative Special Items Conditional on the Reporting (Noisy) Misclassification Signal

The Pricing Model

$$AR_t = \alpha_0 + \alpha_1 \Delta CE_t + \alpha^*_{2,3} \Delta SP_t + \alpha_4 \Delta BV_t + error_t$$



The figure shows the stock return association with negative special items over portfolios formed on the noisy misclassification signal. The pricing model is estimated per portfolio using OLS. Portfolios are formed annually based on the *OIBD* signal. The x-axis represents the portfolio rank. The y-axis represents either $\alpha^*_{2,3}$ estimates in each portfolio or pricing convergence measured as ($\alpha_1 - \alpha^*_{2,3}$). AR_t is value weighted abnormal returns. All definitions of variables are provided in the Appendix.

Chapter 5: Do Analysts Fully Understand the Quality of Negative Special Items When Negative Core Earnings are Misclassified in the Income Statement?

1. Introduction

Street earnings are a special form of GAAP earnings that are modified on the basis of analysts' decision on the inclusions and exclusions of certain components of earnings that are potentially less persistent. Analysts tracking services such as IBES and First Call report street earnings that include or exclude these less persistent earnings components based on the treatment of majority of analysts (Gu and Chen 2004, Baik et al. 2009)[48]. Although the analysts' determination of street earnings inclusions and exclusions is non-uniform, the explicit motive is to filter the street earnings measure from less persistent earnings components. There is evidence that analysts have expertise in processing earnings information to determine the extent of permanence of different earnings component and adjusting street earnings accordingly (Gu and Chen 2004). However, there is also documented evidence that this adjustment process is incomplete, because some expenses excluded from IBES street earnings still have predictive ability for future operating cash flows. While the exclusions contain special items among other exclusions, special items are found to be the most prevalent earnings component that is excluded from street earnings (Doyle et al. 2003)[49].

Special items pose a complicated problem for analysts in arriving at street earnings and also in developing their earlier earnings forecast than other less recurring components of earnings such as discontinued operations and extraordinary items for the following reasons. First, discontinued operations and extraordinary items are reported below earnings from continuing operations on the income statement, but special items are not (Elliot and Hanna 1997). Second, while special items often signify unusual economic conditions related to the firm, their negative composition is suspected to include negative core earnings that have been strategically reported as negative special items (McVay 2006, Frankel and Roychowdhury 2008). This suggests that negative special items have both transitory and core compositions. The former is attributable to the recognition of one-time and unusual events, and the latter is a core component made up by misclassification of negative core earnings.

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[48] Throughout the paper, we assume the "majority rule" for inclusions and exclusions.

[49] Table 1, page (156) in Doyle et al. (2003), shows that the means of total exclusions, excluded special items and other excluded items are 0.03, 0.03, and 0.00, respectively, in their full sample. In a reduced sample that is only restricted to non-zero exclusions, the means are 0.10, 0.09, and 0.02, respectively.

The analysts' treatment of special items inclusions and exclusions in arriving at street earnings is idiosyncratic and deals with special items at the firm-level. Although , in some cases, managers propose inclusions and exclusions of special items and other less recurring items, analysts often make their inclusion/exclusion decision based on their awareness of the persistence of these items. Therefore, the analysts' decision often deviates from the management recommendation (Gu and Chen 2004). In addition, the evidence that links analysts' inclusions/exclusions to management guidance cannot determine who of the analysts or managers are the initiators or followers of the inclusions/exclusions (Christensen et al. 2011). The result is that analysts decide to include special items in street earnings in one firm, but exclude the same items from another; and there is no clear evidence whether the analysts' adjustment process of special items is consistent with the circumstances or incentives leading up to the recognition of special items and hence their potential implications on future earnings[50]. While evidence documents that inclusions are more persistent that exclusions (Gu and Chen 2004), we do know little about the nature and composition of negative special items that promote them for an inclusion/exclusion decision.

In this study, we investigate the inclusion/exclusion decision from the perspective of the underlying compositions of negative special items. More specifically, we examine whether analysts fully understand the nature and quality of negative special items when they adjust actual earnings and whether their future earnings forecast incorporates the actual persistence of components of negative special items. We first decompose negative special items into a shifted negative core earnings component and a purified negative special items component, and then validate our decomposition methodology and our measures using an earnings forecast test and an asymmetric earnings timeliness test. We predict and find that shifted negative core earnings forecast future earnings and abnormal earnings as a core earnings component, and purified negative special items act as a one-time event that contains less information about future earnings. We also find that purified negative special items are much asymmetrically timelier than shifted negative core earnings in recognizing bad news. This is consistent with the transience nature of purified negative special items that is attributable to their use as a channel to recognize

[50] The only exception is Hsu and Kross (2011) who investigate some differences between included and excluded special items. However, their paper does not look into the underlying compositions of negative special items that might justify their inclusion or exclusion.

negative news immediately, and also validates that shifted negative core earnings are fundamentally unrelated to the negative special items classification in the income statement and are indeed a misclassified component.

We next examine the analysts' treatment of negative special items in arriving at street earnings (actual earnings), and whether this treatment aligns with the nature of negative special items compositions. Since analysts include some negative special items and exclude others, we expand our decomposition of negative special items further in order to examine the nature of included and excluded negative special items. We find that included negative special items have higher predictive ability with respect to future operating cash flows, and excluded negative special items do not predict future operating cash flows. Moreover, the shifted component of included negative special items has higher predictive value than the purified component of included negative special items, and each included component has higher predictive value than its excluded counterpart. We also document that while included or excluded negative special items might have shifted and purified components, shifted negative core earnings (purified negative special items) are significantly and positively (insignificantly but negatively) associated with an analysts' inclusion decision. In addition, the analysts' inclusion decision captures the underlying management incentives and economic conditions that lead up to the recognition of negative special items by the firm.

Finally, we assess whether analysts' forecast fully incorporates the actual persistence of negative special items compositions. We follow an approach in the spirit of Chen (2010), Ahmed et al. (2005) and Weber (2009). We estimate actual persistence of earnings components from an actual earnings regression, estimate analysts' implied persistence from a forecast earnings regression and then test the significance of the differences between actual persistence and analysts' implied persistence using an analysts' forecast error regression. Results demonstrate that analysts' treatment of negative special items does not lead to predictable forecast errors, consistent with analysts fully understanding the persistence of negative special items compositions.

Section 2 describes the analysts' adjustment process of negative special items. Section 3 is the sample selection. In section 4, we develop and validate the decomposition approach of negative special items. Section 5 examines the analysts' treatment of negative special items in adjusting actual earnings and developing earnings forecast. Here we develop expanded decomposition of negative special items in the light of negative special items inclusions and exclusions. Section 6 offers concluding remarks.

2. Analysts' Adjustment of Special Items

Analysts adjust GAAP earnings in order to develop a street earnings-metric that excludes less persistent components of earnings. Therefore, the difference between GAAP earnings and street earnings implies the magnitude of total exclusions. It has been found that special items are the primary reason for this difference (Bradshaw and Sloan 2002, Abarbanel and Lehavy 2007, Doyle et al. 2003). In addition, nonrecurring items included in street earnings are also special items and other components of earnings. Therefore, both inclusions and exclusions have special items that analysts, for little known reasons, decide to include or exclude. Prior research suggests that the analysts' adjustment process of special items is linked to management recommendations (Christensen et al. 2011), but that the management influence is also limited to the analysts' beliefs on the persistence of earnings components (Gu and Chen 2004). Moreover, this adjustment process appears to be affected by other factors such as analysts' incentives for promoting stocks with glamour characteristics (Baik et al. 2009).

Given that negative special items are an account that absorbs the transience of earnings via recording most "unusual" or "infrequent" economic events due to accounting conservatism inherent in GAAP (Callen et al 2010), and have also been *misused* to accommodate shifted core losses (McVay 2006); we believe that the *quality* of the firm's negative special items is a major determinant of their inclusions in or exclusions from street earrings. The analysts' adjustment process of negative special items is an income-decreasing (income-increasing) decision when analysts agree on including (excluding) negative special items. If the motive of analysts is to develop a reliable metric of earnings that expresses the magnitude of sustainable earnings, the component of negative special items that contains less information about the future is removed. In addition, firms moving core losses to negative special items are "penalized" by including the shifted negative earnings component in their street earnings (an analysts' income-decreasing decision).

We specifically examine the composition of analysts' included and excluded negative special items. The uncertainty surrounding the economic circumstances and management incentives that lead to recognition of special items, which in turn affect the transience of special items, pose an identification problem for analysts because analysts need to estimate the magnitude of both effects and adjust street earnings accordingly. In addition, since the managers' *misuse* of negative special items to accommodate core losses is a major cause for permanence of negative special items, it is not possible that analysts will be guided by managers in correcting their misclassification. In this setting, analysts' expertise in processing earnings information will be a major determinant of their adjustment decision.

We focus on the analysts' treatment of negative rather than positive special items, because our argument is that the negative special items have core and transitory components that can be linked to shifting (expense-misclassification) and conditional conservatism, while this is not obvious for positive special items. Since we examine the fundamental compositions of special items that nominate them for an inclusion/exclusion decision, we limit our analysis to included and excluded negative special items while controlling for positive special items in our analysis. Moreover, approximately 76% of total special items in our sample are negative special items. This is not surprising given the conservative nature of GAAP that results in negative special items being more prevalent than positive special items.

3. Sample Selection

The full sample consists of firm-year observations from 1989 to 2012 with sufficient Compustat and CRSP data for estimating the negative core earnings level and change regressions. We assign zero to special items if they are missing (Elliott and Hanna 1996, Dechow and Ge 2006), and require unexpected negative core earnings to be non-missing. Following McVay (2006), we drop firms with sales less than $1 million and firms that had a fiscal-year end change. We use a two-digit SIC code in order to identify industry membership and require a minimum of 15 non-missing data per each industry-year combination. Abnormal returns are sized adjusted returns calculated as the CRSP buy-and-hold returns less the buy-and-hold returns on the CRSP equally weighted market portfolio. The measurement of returns commences the fourth month of the fiscal year and ends with the third month of the next the fiscal year.

Following Campbell et al. (2010), we use delisting returns when available and substitute zero for missing monthly returns. The full sample consists of 67,859 firm-year observations. We use the full sample in replicating the main regressions in McVay (2006) using negative core earnings in lieu of net core earnings; and so in our new adaptation of the negative special items decomposition approach.

We then build our IBES sample. We collect actual earnings per share from IBES unadjusted detail actual file, most recent consensus forecast of earnings per share from IBES unadjusted summary file, and primary/diluted indicators from the IBES identifier file to be used when Compustat GAAP earnings per share are matched to IBES street earnings per share[51].We then impose an IBES data requirement for all tests related to analysts. The Compustat-CRSP-IBES reduced sample consists of 46,291 firm-year observations, and 20,782 firm-year observations with non-zero negative special items. The number of observations in any particular test will vary on the basis of the data availability for this particular test.

In order to control for the potential effect of outliers, we winsorize each accounting continuous variable at its first and ninety-ninth percentiles. We report two-tailed significance levels in all regressions. We present descriptive statistics of the main variables in the full sample and the reduced sample in their respective sections in the paper before reporting the regression results.

4. A Direct Decomposition Approach of Negative Special Items

4.1. An Expense-Expense Decomposition Approach

McVay (2006) provides empirical evidence of firms shifting negative core earnings to negative special items in order to increase their net core earnings. The basic McVay's design employs a two-stage regression procedure. In the first stage, expected net core earnings are estimated using a net core earnings expectation model that controls for economic performance. In the second stage, current unexpected net core earnings are regressed on current negative special items. Results in McVay (2006) show a positive association between unexpected net core

[51] The primary/diluted indicator shows whether the firm is followed on a primary or diluted basis. The basis can also change over time. In programming, we ensure that we have the correct basis for the firm in a certain year. This can be done by tracking down each firm and its start date (sdate) in the identifier file. The start date shows the date when the variable first appeared and when the basis later changes.

earnings and negative special items in the second stage regression, consistent with shifting negative core earnings to negative special items in the year a firms reports negative special items. In addition, McVay (2006) shows that the next year unexpected net core earnings changes, estimated using an expectation model of net core earnings change, are decreasing with current year negative special items. This later result is consistent with a reversal of the improvement in net core earnings when negative core earnings return to core earnings in the next period[52,53].

Shifting results in a misclassification of negative core earnings, because a batch of negative core earnings is buried in negative special items in the income statement. Consequently, negative special items, that are less persistent by definition, become contaminated with more persistent negative earnings. Building on the McVay's approach to classification shifting, Abdalla and Clubb (2015) employ a decomposition approach of special items that breaks down the special items into a more persistent component due to shifting and a less persistent component representing the genuine special items that are free of shifting[54]. In this paper, we employ a similar methodology that validates the decomposition approach and is based on a negative core earnings variant of the McVay's model. Specifically, we replicate the analysis in McVay, but we replace net core earnings with only negative core earnings. Therefore, our analysis is directly focused on the association between unexpected negative core earnings and negative special items. We believe that this expense-expense approach provides more direct evidence to classification shifting than an observed association between net core earnings and negative special items, which implicitly infers the negative core earnings transfer. We expect a contemporaneous negative association between unexpected negative core earnings and negative special items, because shifting increases negative special items and decreases unexpected negative core earnings. We expect a positive association between next year unexpected negative core earnings changes and current negative special items, that is a result of the reversal of the artificial efficiency and reduction in negative core earnings in the current year.

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[52] McVay (2006) shows that the reversal is less pronounced when the firm reports negative special items in the current and next years.

[53] Throughout the paper, negative special items are multiplied by -1 in our adaptations of the McVay models, in order to be comparable to McVay (2006). In all other regressions, negative special items are negative data values.

[54] Abdalla and Clubb (2015) is based on chapter three of this thesis.

The negative core earnings levels and changes expectation models are as following:

$$NCE_t = \eta_0 + \eta_1 NCE_{t-1} + \eta_2 ATO_t + \eta_3 ACC_{t-1} + \eta_4 ACC_t + \eta_5 \Delta SALE_t + \eta_6 NEG\Delta SALE_t + \xi_t \quad (13)$$

$$\begin{aligned}\Delta NCE_t = \theta_0 + \theta_1 NCE_{t-1} + \theta_2 \Delta NCE_{t-1} + \theta_3 \Delta ATO_t + \theta_4 ACC_{t-1} + \theta_5 ACC_t + \theta_6 \Delta SALE_t \\ + \theta_7 NEG\Delta SALE_t + \varepsilon_t\end{aligned} \quad (14)$$

where NCE_t is negative core earnings measured as the sum of cost of goods sold and selling and administrative expenses divided by sales. If the values are missing, we calculate negative core earnings as the difference between sales and operating income before depreciation divided by sales. The data values for NCE_t are positive. ATO_t is assets turnover ratio measured as sales divided by average net operating assets. ACC_t is operating accruals measured as net income before extraordinary items minus cash flow from operations divided by sales. $\Delta SALE_t$ is the percentage change in sales measured as current sales minus lagged sales and divided by lagged sales. $NEG\Delta SALE_t$ is the negative percentage change in sales measured as $\Delta SALE_t$ when $\Delta SALE_t < 0$, and zero otherwise. The models are estimated for each industry-year combination and excluding firm i from the estimation. We report the models fit statistics in Table 1.We predict the coefficients to be of relatively similar magnitude but opposite direction to those in the original McVay models[55].

The association between unexpected negative core earnings and negative special items is tested using the following models:

$$UNCE_t = \phi_0 + \phi_1 NSI_t + \zeta_t \quad (15)$$

$$U\Delta NCE_{t+1} = \varphi_0 + \varphi_1 NSI_t + \upsilon_{t+1} \quad (16)$$

[55] The only exceptions are NCE_{t-1} and ΔNCE_{t-1}. Both of the lagged values are predicted to be similar in direction to the AR(1) coefficients in McVay (2006). For other explanatory variables, we predict the opposite direction. For example, if ACC_t is positively related to net core earnings in McVay (2006), we predict it to be negatively related to the expense component of core earnings in our analysis, that is negative core earnings.

where $UNCE_t = NCE_t - E\left(NCE_t\right)$, $U\Delta NCE_{t+1} = \left[\Delta NCE_{t+1} - E\left(\Delta NCE_{t+1}\right)\right]$, and $E\left(NCE_t\right)$ and $E\left(\Delta NCE_{t+1}\right)$ are expected negative core earnings levels and expected negative core earnings changes from equation (1) and equation (2), respectively. NSI_t is negative special items divided by sales. Negative special items are multiplied by -1 in this regression. We estimate the regressions using OLS, and report the results in Table 2.

We then adopt a similar decomposition technique, as in Abdalla and Clubb (2015) that is relevant to the new adaptation of the McVay's core earnings model. First, we regress unexpected negative core earnings on negative special items for each industry and year combination. Since shifting in this case results in a negative coefficient on the negative special items that is between zero and negative one, we set all positive industry-year coefficients to be equal to zero (approximately 44.9% of the coefficients are positive), and set all negative industry-year coefficients that are less than negative one to be equal to the maximum bound of shifting, which is negative one (3.6% of the negative coefficients are less than negative one)[56,57]. Second, we multiply the negative industry-year coefficients by reported negative special items of firms in the relevant industry-year combination in order to measure shifted negative core earnings, $SNCE_{i,t}$, at the firm level. We then subtract $SNCE_{i,t}$ from reported negative special items in order to measure purified negative special items, $PNSI_{i,t}$ .We call this level of decomposition of negative special items; CLASSIFICATION DECOMPOSITION (CLDE hereafter), in order to differentiate it from other levels of decomposition in the next sections of the study. In Figure 1, we show the means of the two components of negative special items over years.

Table 1 results show that the magnitude and direction of all coefficients are consistent with the results in McVay (2006) and our adaptations of the models. In Panel A of Table 1, negative core earnings are positively related to their lagged values, higher with assets turnover ratio and

[56] Recall that , in the presence of shifting, negative special items have shifted negative core earnings and special items charges that are free of shifting. Therefore, a dollar increase in negative special items results in a decline in unexpected negative core earnings relative to the proportion of shifted negative core earnings in special items. If special items are entirely shifted negative core earnings, we expected the coefficient to be equal to negative one. Negative coefficients that are less than negative one might be due to inevitable measurement error in expected negative core earnings. Restricting these coefficients to be zero does not qualitatively affect all related results in the next sections.

[57] The counterpart negative industry-year coefficients when using a net core earnings models are 46%, and the counterpart extreme positive coefficients that are higher than one are 3.91% in Abdalla and Clubb (2015).

lagged accruals; and lower with current accruals, sales growth and negative sales growth. Mean coefficients using OLS and median coefficients using quintile regression are consistent. In untabulated results, we also run a censored regression (Tobit model) and the results are very similar to the OLS results. This gives us comfort in using OLS in the first stage regression. For sake of brevity, we only present the OLS results here. Adjusted R^2 are 76% and 73% in the OLS regression and quintile regression, respectively. In Panel B of Table 1, negative core earnings changes are negatively related to lagged negative core earnings levels and changes, higher with lagged accruals, and lower with assets turnover changes, current accruals, sales growth and negative sales growth. Mean and median coefficients are consistent, except that negative sales growth is insignificant using OLS and significant using quintile regression. Adjusted R^2 are 35% and 31% in the OLS regression and quintile regression, respectively.

[Insert Table 1 here]

Table 2 shows results supporting the existence of negative core earnings misclassification. Panel A of Table 2 reports the main test results. Panel B of Table 2 reports on whether the relation between unexpected negative core earnings and negative special items, which is observed in Panel A, is attributable to misclassification or efficiency in negative core earnings as a result of special items reporting. In Panel A, a dollar of negative special items in the entire sample (negative special items subsample) decreases an average of 4.2 (3.8) cents of negative core earnings, consistent with a portion of reported negative special items being shifted negative core earnings. In Panel B, the next year unexpected negative core earnings changes are increasing with current negative special items, consistent with a reversal of the artificial reduction in negative core earnings that is a result of misclassification. When we require next year negative special items to be non-zero in the regression in order to allow for the possibility to shift in the next period, which is expected to minimize the reversal, the results show that the reversal becomes insignificant. Overall, the results support our alternative adaptation of McVay (2006).

[Insert Table 2 here]

Figure 1 displays the magnitude of the negative special items components over years. Note that the entire negative special items are purified and have no shifted component when firms report negative special items as a result of poor performance rather than shifting (those with positive coefficients in the decomposition industry-year regressions). When firms shift, negative special items contain shifted negative core earnings and purified negative special items components (those with negative coefficients in the decomposition industry-year regressions). Also, in some cases negative special items can be entirely shifted negative core earnings. The figure shows that the non-zero mean values of shifted negative core earnings are relatively stable in comparison to purified negative special items. The magnitude of purified negative special items is always higher than shifted negative core earnings. In years 2001 to 2003, purified negative special items reach a peak. This is concurrent with a warning issued by SEC in 2001 about the use of pro-forma earnings by managers that exclude non-recurring expenses. This SEC action could possibly have restricted the misclassification during this time, especially because shifted negative core earnings are significantly lower in 2002. After 2003, purified negative special items decline significantly, until climbing back in 2008 to just below their 2002 peak during the financial crisis period.

[Insert Figure 1 here]

4.2. Validation of the Decomposition Approach and Prediction of Future Earnings

Reported negative special items pool expenses resulting from one-time events, which are generally not frequently recurring and therefore less persistent, and expenses resulting from strategic reporting of negative core earnings as negative special items. In order to validate the identification of the two unobservable components of negative special items on the basis of our direct decomposition approach, we test their forecasting abilities for future profitability (future earrings) and future excess value (abnormal earnings). Specifically, we estimate the following regressions:

$$E_{t+1} = \omega_0 + \omega_1 CE_t + \lambda_0 NSI_t + \omega_3 OTE_t + \omega_4 BV_t + \vartheta.IY + \zeta_{t+1} \tag{17}$$

$$E_{t+1} = \omega_0 + \omega_1 CE_t + \lambda_1 SNCE_t + \lambda_2 PNSI_t + \omega_3 OTE_t + \omega_4 BV_t + \vartheta.IY + \zeta_{t+1} \tag{18}$$

E_{t+1} is the dependent earnings variable measured as earnings (earnings before extraordinary items and discontinued operations), or abnormal earnings (earnings before extraordinary items and discontinued operations minus the multiplication of cost of capital and beginning book value) divided by sales[58]. CE_t is core earnings measured as operating income before depreciation divided by sales, OTE_t is earnings other than core earnings and negative special items measured as $(E_t - CE_t - NSI_t) / SALE_t$, BV_t is ending book value divided by sales, and IY is a set of indicator variables that represent the industry membership and the year.

We predict different forecasting properties for the two negative special items components. If $SNCE_t$ extracts shifted negative core earnings from negative special items leaving out $PNSI_t$ as a measure of purified negative special items, we expect $\omega_1 = \lambda_1$ and $\omega_1 > \lambda_2$. We estimate the regressions using OLS and report the results in Table 3. Panel A reports the regressions results for forecasting earnings and Panel B reports the regression results for forecasting abnormal earnings. In each regression, we first regress the earnings variable on core earnings and negative special items (or their components), and then estimate the regression using the full specification as in equation (5) and equation (6). Since both results are consistent, we discuss only the full specification results and the variables of interest.

Table 3 Panel A reveals that the mean of special items is negative, consistent with the literature. Purified negative special items are larger in magnitude than shifted negative core earnings. Earnings other than core earnings and negative special items, OTE_t, are negative on average. Table 3 Panel B results show that the coefficient on core earnings is 0.839 and highly significant $(t = 65.35)$ and the coefficient on negative special items is 0.282 and highly significant $(t = 7.97)$. The value of the negative special items coefficient is approximately one third of the value of the core earnings coefficient. The difference between both coefficients is statistically different from zero (F−value =188.64, P−value = 0.00). In contrast, the results show that when negative special items are decomposed, $SNCE_t$ has a pronounced relation with future earnings, which is statistically indifferent from that of reported core earnings (F−value =0.40, P−value = 0.529). On the other hand, the coefficient on $PNSI_t$ is clearly lower than that on core earnings and the difference is statistically significant (F−value =152.38, P−value = 0.00).

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[58] We assume a fixed 12% cost of capital consistent with Barth et al (1999)

Table 3 Panel C results for the abnormal earnings regression are consistent with the results in Table 3 Panel A. Before decomposition of negative special items, the results show that negative special items forecast future abnormal earnings, but their forecasting coefficient is significantly lower than the coefficient on core earnings. When negative special items are decomposed, the coefficient on the shifted negative core earnings composition is nearly twice that on the purified negative special items composition $(\lambda_1 = 0.686, t = 2.82 \text{ and } \lambda_2 = 0.232, t = 6.06)$. Moreover, the coefficients on core earnings and the shifted negative core earnings (purified negative special items) composition of negative special items are statistically indifferent (different).

In summary, negative special items have a forecasting value with regard to future (abnormal) earnings that is statistically less than that of core earnings. When negative special items are decomposed into a shifted negative core earnings component and a purified negative special items component using our direct decomposition approach, the forecasting coefficient on the former component is almost as large as the coefficient on core earnings. In contrast, the forecasting coefficient on purified negative special items is much lower in value and statistically less than core earnings, consistent with less persistent implications for future earnings. This implies that $SNCE_t$ captures the permanence of negative special items that is due to strategic reporting of special items and $PNSI_t$ reflects the transience of negative special items that is consistent with their presumed nature.

[Insert Table 3 here]

4.3. Validation of the Decomposition Approach and Asymmetric Timelines of Negative Special Items compositions

Under (conditional) conservative accounting, bad news accrues in earnings in a timelier fashion relative to good news (Basu 1997). This asymmetrically timely loss recognition is generally facilitated via the recognition of negative special items (Frankel and Roychowdhury 2008 and Callen et al. 2010) and increases the transience of special items (Heflin et al. 2014). For example, the timely recognition of write-offs and restructuring charges in response to anticipation of a negative shock to the firm's future cash flows is generally reported as negative special items in the income statement. Consistent with this notion, Riedl and Srinivasan (2010) find that reporting negative special items is more preponderant than positive special items, and Callen et al. (2010) provide evidence of asymmetric timeliness of special items and that negative special items act as a proxy for negative news regarding the firm's future cash flow.

Together with the evidence of negative core earnings shifting to negative special items in McVay (2006) and our decomposition approach, we expect that timely loss recognition is more pronounced in the component of negative special items that represents purified negative special items, $PNSI_t$, than the component of negative special items that is made up by shifting, $SNCE_t$. In order to run this validation test, we use an adaptation of the Basu (1997) regression of earnings on abnormal returns (news proxy) as a measure of timely loss recognition, but we replace earnings with special items or different components of special items as following:

$$SPECIAL_t = \beta_0 + \beta_1 D_t + \beta_2 AR_t + \beta_3 AR_t * D_t + \varepsilon_t \qquad (19)$$

$SPECIAL_t$ is the special items component through which accounting conservatism is manifested. We estimate a set of regressions using total special items, TSI_t, positive special items, PSI_t, negative special items, NSI_t, and our main interest variables: $PNSI_t$ and $SNCE_t$. AR_t is abnormal returns measured as the difference between buy-hold returns minus the buy-hold returns on the CRSP equally weighted market index. The measurement of returns begins the fourth month of the fiscal year and ends three months after the end of the fiscal year. We use delisting returns when available and substitute zeros for missing monthly returns (Campbell et al. 2010).[59] D is an indicator variable that is equal to one when $AR_t < 0$ and zero otherwise. β_2 captures the timeliness of $SPECIAL_t$ with respect to good news, and β_3 captures the asymmetric timeliness of $SPECIAL_t$ with respect to bad news. We use OLS regressions and report the estimated coefficients in Table 4. We also estimate censored regressions (TOBIT) for positive and negative special items dependent variables that are censored at zero, and find that all results are consistent with the OLS results; therefore we choose to report only the OLS results for sake of brevity.

[59] Results are not sensitive to excluding missing returns.

Table 4 Panel A results show that the good news coefficient β_2 is very small in all regressions. The asymmetric timeliness coefficient β_3 is positive and significant when we use total special items (gains and losses) or only negative special items as the earnings dependent variable ($\beta_3 = 0.120, t = 27.59$ in the total special items regression, and $\beta_3 = 0.122, t = 28.68$ in the negative special items regression). The similar coefficients magnitude is not surprising, given that approximately 76% of the total special items are negative special items. The intercept β_0 is negative and significant meaning that some prior years' bad news is incorporated in the current year total or negative special items. When only positive special items are used as the dependent earnings variable, β_3 becomes negative and insignificant ($\beta_3 = -0.001, t = -1.63$). The intercept also becomes positive and significant with a lower value, which indicates that less good news from prior years are incorporated in positive special items. These results are consistent with our discussion that negative special items are an important means of conditional conservatism.

Table 4 Panel B show more interesting results that support our decomposition of negative special items. Using the purified negative special items component, $PNSI_t$, as the dependent earnings variable, the results show an asymmetric timeliness coefficient $\beta_3 = 0.127$ and an intercept $\beta_0 = -0.042$. When we use the shifted negative core earnings component of the negative special items, $SNCE_t$, the coefficient β_3 decreases to a very small value of only 0.009 in the same sample. That is, the asymmetric timelines coefficient is approximately 14 times lower in the case of $SNCE_t$. Also, the intercept decreases to only -0.005. The adjusted R^2 sharply declines from 5.7% in the $PNSI$ regression to only 1.7% in the $SNCE$ regression.

These results provide further validation of our identification of the negative special items compositions by showing that $PNSI_t$ is the underlying negative special items composition that represents the downward revision in anticipated future cash flows and induces an asymmetrical timeliness property, but $SNCE_t$ has very small asymmetric timelines.

[Insert Table 4 here]

5. Analysts' Treatment of Negative Special Items Compositions in Street Earnings

5.1 Extended Decomposition of Negative Special Items between Street Earnings Inclusions and Exclusions

The analysts' differential treatment of special items provides an interesting setting to test the properties of the negative special items that are included in and excluded from street earnings. Given our firm-level decomposition of negative special items, a firm's negative special items included in (excluded from) street earnings can have a shifted component and a purified component. While the motivation of analysts is to include (exclude) negative special items that are more persistent (less persistent), it is interesting to investigate whether the differential treatment of negative special items is attributed to the differential properties of the negative special items compositions. In other words, we test whether the extant empirical evidence that analysts having expertise in identifying more persistent negative special items is justified by the fundamental composition of negative special items. Towards this goal, we first identify two groups of negative special items on the basis of street earnings adjustment such that:

$$NSI_t = INCNSI_t + EXCNSI_t \tag{20}$$

$INCNSI_t$ is negative special items included in street earnings and measured as negative special items if street earnings is equal to GAAP earnings, and zero otherwise. $EXCNSI_t$ is negative special items excluded from street earnings and measured as negative special items if street earnings > GAAP earnings, and zero otherwise. This level of decomposition is meant to *attach a label to* the negative special items as per the analysts' treatment. We call this decomposition ANALYSTS DECOMPOSITION (ANDE hereafter).

Given that an inclusion/exclusion decision is not expected to apply on the entire amount of negative special items of an individual firm, such that analysts decide to include either all negative special items of the firm or exclude them, but rather applies their decision on specific components within the total negative special items, we allow for an extended decomposition of negative special items that combines both CLDE and ANDE as following:

$$NSI_t = INCSNCE_t + INCPNSI_t + EXCSNCE_t + EXCPNSI_t \tag{21}$$

$INCSNCE_t$ ($EXCSNCE_t$) is shifted negative core earnings included in (excluded from) street earnings and measured as shifted negative core earnings, $SNCE_t$, if negative special items are included in (excluded from) street earnings, and zero otherwise. $INCPNSI_t$ ($EXCPNSI_t$) is purified negative special items included in (excluded from) street earnings and measured as purified negative special items, $PNSI_t$, if negative special items are included in (excluded from) street earnings, and zero otherwise. This extended level of decomposition further tags the shifted and purified compositions within included and excluded negative special items. We call this ANALYSTS−CLASSIFICATION DECOMPOSITION (ANCLDE hereafter).

An alternative approach to present the ANCLDE level is to *sort* negative special items between $INCNSI_t$ and $EXCNSI_t$ on the basis of whether negative special items are contaminated by shifted negative core earnings $SNCE_t$ such that:

$$NSI_t = ICONTAM_t + ICLEAN_t + ECONTAM_t + ECLEAN_t \tag{22}$$

where $ICONTAM_t$ ($ECONTAM_t$) is negative special items included in (excluded from) street earnings and contaminated by shifted negative core earnings. We measure $ICONTAM_t$ ($ECONTAM_t$) as NSI_t if NSI_t are included in (excluded from) street earnings and $SNCE_t \neq 0$, and zero otherwise. $ICLEAN_t$ ($ECLEAN_t$) is negative special items included in (excluded from) street earnings and are entirely free of any shifted negative core earnings[60]. We measure $ICLEAN_t$ ($ECLEAN_t$) as NSI_t if NSI_t are included in (excluded from) street earnings and $SNCE_t = 0$, and zero otherwise. We call this sorting, ANALYSTS−CLASSIFICATION SORTING (ANCLSO hereafter). Although we expect consistent results using both ANCLDE and ANCLSO, we expect results using ANCLDE to be more pronounced. This is because ANCLDE is more directed to the compositions of negative special items, and as mentioned earlier, analysts' decision of inclusions and exclusions applies on specific items within special

[60] Recall that the CLDE level defines negative special items as being entirely purified and has no shifted negative core earnings when the negative special items have a positive coefficient in the decomposition regression. In this case, negative special items are reported by the firm as a result of poor performance rather than shifting.

items rather than being an "all-or-none" decision. In Figure 2 we present the different earnings components used in the analysis as per the level of negative special items decomposition.

[Insert Figure 2 here]

5.2 Future Cash Implications of Negative Special Items Extended Compositions

Doyle et al. (2003) argue that future cash flows are a desirable metric to test potentially "mislabeled nonrecurring expenses", because cash flows are less vulnerable to traditional earnings management. Therefore, the association of a negative special items component with future cash flow determines the degree of permanence of the component as it recurs in the future and consumes cash flows. Our first set of tests of the analysts' treatment of negative special items examines the relation between future cash flows and different decomposition levels of negative special items identified in the text. We use a regression of the following form:

$$OCF_{t+1} = \gamma_0 + \gamma_1 EBSI_t + \rho SPECIAL_t + \varepsilon_{t+1} \tag{23}$$

OCF_{t+1} is one year-ahead operating cash flow and measured as operating cash flow divided by total assets. $EBSI_t$ is earnings before special items and measured as operating earnings per share divided by assets per share, and $SPECIAL_t$ is the special items components as per each decomposition level.

We estimate the future cash flows regressions using OLS and show the results in Table 5. Each Panel in Table 5 corresponds to a decomposition (or sorting) level. We run the regressions for a sample of all special items firms and a restricted sample of only negative special items firms. Though CLDE is not an analysts' decomposition level, we show the results of this decomposition for two reasons. First, all regressions here (and in next sections) are based on reduced samples after merging with IBES data, so it is important to show that the properties of shifted negative core earnings and purified negative special items, as per our decomposition measurement approach applied on the initial sample, hold in these samples. Second, the results from CLDE provide a benchmark for the ANCLDE level, which is the most expanded analysts' decomposition level.

Table 5 Panel A reports descriptive statistics for the main variables. It shows that the magnitude of negative special items excluded from street earnings is higher than the magnitude of those included in street earnings, consistent with the literature. Table 5 Panel B shows results of the CLDE level. In the special items firms sample (A), results indicate that a dollar of earnings before special items predicts 0.538 dollars of future operating cash flow. With regard to special items, shifted negative core earnings predict lower future operating cash flows and have a significant coefficient of 0.151, purified negative special items have a small and insignificant coefficient of 0.017, and positive special items have a negative and significant coefficient of −0.256. When the sample is restricted to only negative special items, results remain consistent except that purified negative special items become marginally significant at the 10% level with a coefficient of 0.023. These results further validates the original CLDE level by showing that the predictive ability of shifted negative core earnings is not limited to the forecast of earnings, and if operating cash flows are the only metric for evaluating the predictive ability of misclassified expenses as argued by Doyle et al. (2003), our CLDE results of the differential predictive properties of decomposed negative special items hold in this setting.

We now move to the analysts' adjustment of street earnings in order to see if there are any differences between the negative special items that analysts choose to include in street earnings, and those items excluded from street earnings[61]. Table 5 Panel C shows interesting results with regard to the analysts' inclusion/exclusion choice. When negative special items are decomposed into included and excluded negative special items, it appears that only included negative special items predict future operating cash flows. The included negative special items have a highly significant coefficient of 0.132 (0.138) in the special items sample (negative special items sample). Excluded negative special items have a small and insignificant coefficient of 0.011 (0.016) in the special items sample (negative special items sample). The similarity between the coefficient of included (excluded) negative special items in Panel C and shifted negative core earnings (purified negative special items) in Panel B is "eye catching". While this is appealing by itself, it does not provide evidence of an analysts' inclusion/exclusion choice being taken on the

[61] Earnings before special items coefficient and positive special items coefficient are relatively consistent across all levels of decomposition in Table 5. To be more focused on our main interest variables, which are the negative special items components, we discuss in text the coefficients on the different negative special items components in subsequent panels of Table 5.

basis of the underlying core and transitory compositions of negative special items. We provide this latter evidence in Panel D and Panel E among other results in the next sections.

We now report results from the ANCLDE level, which is an intersecting decomposition level of the CLDE and ANDE levels. Table 5 Panel D shows a very interesting pattern on the coefficients of negative special items components. Both included shifted negative core earnings and included purified negative special items have significant coefficients and their excluded counterparts have insignificant coefficients. The coefficient on included shifted negative core earnings is 0.630 (0.637), and insignificantly different from the coefficient on earnings before special items, which is equal to 0.539 (0.526) in the special items firms sample (negative special items sample)[62]. Included purified negative special items have a significant coefficient of 0.094 (0.10) in the special items sample (the negative special items sample) which is much lower than the included shifted negative core earnings coefficient. We interpret this such as the included shifted negative core earnings component being a manager's misclassified core earnings component that originally belongs to earnings before special items rather than special items. Therefore, the included shifted negative core earnings are an analysts' adjustment of the managers' misclassification. On the other hand, included purified negative special items are an analysts' selection of real special items that are higher in their predictive ability of next period cash flows than other real special items, which are excluded. For example, a write-off or restructuring charge, that arises due to changes in economic conditions might be associated with lower cash flows in the next year, and hence included by analysts for reasons other than shifting. Another intuitive example is that a write down of inventory in the current year is expected to be related to subsequent cost of goods sold because the written-down ending inventory is carried forward to the next period and becomes a part of subsequent cost of goods sold[63]. In contrast, One-time losses from sale of assets or merger and acquisition losses might not have significant implications for future cash flows, therefore excluded by analysts. This is consistent with the evidence of differential predictive abilities of categories of special items documented in Riedl and Srinivasan (2010).

[62] Untabulated Wald tests report *F- value*=0.10, and P-value 0.7491 in the special items sample, and F value=0.15, and P-value= 0.6972 in the negative special items sample.

[63] Ohlson (2006) argues that this property is one of the drawbacks that stems from the GAAP reliance on a balance sheet approach rather than an income statement approach, and will induce permanence in some items of special items, apparently without any management intention to use them as device for shifting core expenses.

Though excluded negative special items corresponding to shifted negative core earnings and purified negative special items have insignificant coefficients, the coefficient on excluded shifted negative core earnings is still higher than that on excluded purified negative special items. The exclusion choice of shifted negative core earnings might be due to analysts' belief that although this batch of shifted losses is recurring, the likelihood of its recurrence is not high enough to warrant its inclusion in street earnings. On the other side, excluded purified negative special items are more consistent with transitory losses that are real special items. In any event, the analysts' inclusion and exclusion choices appear to be successful in picking up the more persistent batches of losses that are shifted core losses or special items associated with future performance.

Table 5 Panel E show results of the ANCLSO level. Though the negative special items coefficients exhibit a decreasing pattern as in Panel C, some interesting results emerge. The only significant coefficient on negative special items components is the coefficient on included contaminated negative special items, which are basically negative special items that accommodate shifted negative core earnings. Excluded contaminated negative special items become marginally significant at the 10% level only when the sample is restricted to negative special items firms. Together with results from Panel D, the analysts' inclusion decision of purified negative special items might be also due to a less ability to isolate purified negative special items from shifted negative core earnings when negative special items are contaminated with shifting, or as in Panel D, because some of the purified items are more persistent by themselves. Another interesting result is the significant drop in the coefficient attached to included contaminated negative special items in Panel E in comparison to the included shifted negative core earnings coefficient in Panel D, which indicates how the aggregation of the core (shifted) and transitory (purified) components of negative special items affects the persistence of the negative special items measure.

Taken as a whole, the future cash flow regressions results indicate analysts' ability to process negative special items information and include in street earnings the more dominant shifted and purified components of special items.

[Insert Table 5 here]

5.3 Determinants of Inclusions and Exclusions of Negative Special Items Compositions

So far, our results reveal that analysts include in (exclude from) street earnings selective shifted and purified components of negative special items, and that each included component appears to have higher association with future cash flows than its excluded counterpart. Next, we more explicitly investigate the relation between the analysts' inclusion/exclusion decision and the compositions of negative special items after controlling for other factors that are likely to be associated with the analysts' decision. Specifically, we estimate the following analysts' decision model:

$$\begin{aligned} INCLUSION_t = {} & \kappa_0 + \kappa_1 SHIFTED_t + \kappa_2 PURIFIED_t + \kappa_3 SMOOTH_t + \kappa_4 COV_t \\ & + \kappa_5 FRE_t + \kappa_6 HIS_t + \kappa_7 BTM_{t-1} + \kappa_8 MER_t + \kappa_9 ROA_{t-1} + \kappa_{10} MAG_t + \xi_t \end{aligned} \quad (24)$$

$INCLUSION_t$ is an indicator variable coded as one if negative special items are included in street earnings, and zero if negative special items are excluded from street earnings. $SHIFTED_t$ is an indicator variable equal to one if shifted negative core earnings have a non-zero value, and zero otherwise. $PURIFIED_t$ is an indicator variable equal to one if purified negative special items have a non-zero value, and zero otherwise. On average, a successful analysts' decision will have the tendency to include shifted negative core earnings in street earnings and exclude purified negative special items from street earnings. In this case, we expect κ_1 to be positive and κ_2 to be negative. We include other determinants and factors that might be associated with the analysts' decision. We include a variable, $SMOOTH_t$, that controls for accounting discretion and use of accruals to smooth earnings (Bowen et al. 2008, Leuz et al. 2003). $SMOOTH_t$ is measured as the ratio of volatility of operating cash flow to volatility of earnings (after special items and before extraordinary items), where volatility of operating cash flow or earnings is measured as the standard deviation of the firm's rolling five-year window (minimum of three non-missing observations). Ratios higher than one indicate higher volatility of operating cash flows relative to earnings, which is consistent with the use of accruals to smooth earnings. Since most special items are accruals (Dechow and Ge 2006), we expect the analysts' propensity to include negative special items in street earnings to be increasing with $SMOOTH_t$. We include an analysts coverage variable, COV_t, measured as the natural logarithm of the number of analysts following the firm. We expect the coefficient on COV_t to be negative if the analysts believe that higher analysts coverage serves a monitoring role in mitigating the managers' misuse of negative special items to bury core losses. We include two variables that control for the firm's repeated negative special items reporting over the past two years, FRE_t, and the analysts history of treating the firm's negative special items when arriving at street earnings over the same time period, HIS_t. We measure FRE_t as an indicator variable equal to one if the firm reported negative special items in years $t-1$ and $t-2$, and zero otherwise. We measure HIS_t as an indicator variable equal to one if the analysts chose to include the firm's negative special items in years $t-1$ and $t-2$, and zero otherwise. We do not have a priori expectation on the coefficient of these variables.

We add other variables that capture the reporting of negative special items by firms due to unusual events, which are expected to increase the transience of negative special items. We add the book to market ratio at the beginning of the year, BTM_{t-1}, because higher book to market ratios are positively associated with significant impairment losses, consistent with assets being written-off when their book values are higher than their market values (Francis et al. 1996). We add MER_t to control for significant mergers and acquisitions-related costs, which are more likely reported as negative special items. We measure MER_t as an indicator variable equal to one if annual acquisitions are higher than 20 percent of the firm's beginning of the year total assets, and zero otherwise (Baber et al. 2011). We also add the return on asset ratio at the beginning of the year, ROA_{t-1}, because poor past performance is associated with larger impairment losses (Francis et al. 1996). We expect to observe negative coefficients on BTM_{t-1}, MER_t, and ROA_{t-1} if analysts understand the transitory nature of negative special items associated with these variables. We add a variable, MAG_t, that controls for the magnitude of negative special items. Large negative special items often include large restructuring charges, impairment losses and write-offs associated with higher conditional conservatism and lower negative special items persistence. However, significant large negative special items can be also due to misclassification of negative core earnings (Frankel and Roychowdhury, 2008).We measure MAG_t as an indicator variable equal to one if the firm reported negative special items higher than the annual cross section mean of negative special items firms, and zero otherwise, but because of the competing effects, we do not have a priori expectation on the coefficient of the variable.

Since the analysts' decision model is a dichotomous outcome model, estimating the model using ordinary least square linear probability (OLS-LPM) results in unbiased coefficients that are directly interpreted as probabilities, but the standard errors from the model are heteroscedastic (Stone and Rasp 1991).Therefore, in order to mitigate heteroscedasticity, we estimate the model using a logistic regression (LOGIT). Nevertheless, we also report the OLS-LPM results to see if they differ from the LOGIT results. We report the LOGIT coefficient estimates and their marginal significance and the OLS-LPM coefficients in Table 6.

Table 6 Panel A reports descriptive statistics. Table 6 Panel B results show that all estimated coefficients have the expected sign and are significant at conventional levels with the exception of the coefficient on $PURIFIED_t$, which has the predicted sign but is insignificant. The intercept is negative, consistent with an average trend to exclude negative special items from street earnings. It appears that analysts are more likely to include shifted negative core earnings hidden in negative special items to correct for the expense misclassification, and also negative special items that are used to smooth earnings. The negative coefficient on purified negative special items suggests some tendency to exclude them from street earnings, but the coefficient is insignificant. Nevertheless, this insignificance can be justified on the basis that although purified negative special items are on average less persistent, our results in Table 5 reveal that they have an included persistent component. This might have affected the significance of the negative relation between the inclusion decision and purified negative special items in the logistic regression.

We find that analysts perceive analysts coverage as a monitoring device for the manager's misuse of negative special items and tend to exclude negative special items for firms with higher analysts coverage. Additionally, analysts are less likely to include negative special items when the firm repeatedly reports negative special items over the last two years, but are more likely to include them if they have been included by analysts over the same period. Consistent with our expectations, we find that the variables associated with more transitory negative special items are negatively associated with the inclusion decision. The OLS-LPM estimation shows consistent results to the LOGIT model.

Overall, the results of analysts' decision model indicate that the analysts' treatment of negative special items in arriving at street earnings is guided by their awareness of the motivations and circumstances associated with negative special items reporting.

[Insert Table 6 here]

5.4 Does Analysts' Earnings Forecast Fully Incorporate the Actual Persistence of Negative Special Items Compositions?

5.4.1 Main results

Our results suggest that negative special items components that analysts choose to include in street earnings dominate their excluded counterparts in forecasting future operating cash flows. In addition, the analysts' inclusion/exclusion decision of negative special items is responsive to the management incentives versus economic conditions leading up to negative special items reporting. In our next tests, we complement our analysis by examining whether the analysts implied expectations of persistence of negative special items compositions reflected in their earnings forecast just prior to earnings announcement are consistent with the actual persistence implied by the earnings process. It is reasonable to test this relation at the forecasting stage, because the existence of less recurring items such as special items is already known and reflected in analysts' earlier forecasts before actual earnings are reported. Hence, the actual amount of the less recurring items rather than their existence may come at a surprise when actual earnings are announced (Gu and Chen 2004).

We estimate the actual persistence of each negative special items composition as per its estimated coefficient in the following earning regression:

$$\begin{aligned} STR_{t+1} = {} & \pi_0^{STR} + \pi_1^{STR} EBSI_t + \phi_1^{STR} INCSNCE_t + \phi_2^{STR} INCPNSI_t + \phi_3^{STR} EXCSNCE_t \\ & + \phi_4^{STR} EXCPNSI_t + \zeta_{t+1}^{STR} \end{aligned} \tag{25}$$

where STR_{t+1} is one year ahead-street earnings (i.e. actual earnings) and measured as the IBES reported actual earnings per share divided by assets per share. All other variables were defined before.

Next, we estimate the implied persistence weights that analysts attach to each negative special items composition as per its estimated coefficient in the following analysts forecast regression:

$$\begin{aligned} ANF_{t+1} = \pi_0^{ANF} + \pi_1^{ANF} EBSI_t + \phi_1^{ANF} INCSNCE_t + \phi_2^{ANF} INCPNSI_t + \phi_3^{ANF} EXCSNCE_t \\ + \phi_4^{ANF} EXCPNSI_t + \zeta_{t+1}^{ANF} \end{aligned} \tag{26}$$

where ANF_{t+1} is one year ahead-analyst consensus forecast (i.e. forecast earnings) and measured as the last median consensus forecast of actual earnings per share issued before the earnings announcement date.

The relations between ϕ_n^{STR} and ϕ_n^{ANF} determine whether analysts are more or less optimistic in their inclusions and exclusions of negative special items and the weights they attach to each included/excluded negative special items composition. In order to test for analysts' efficiency, we subtract equation (14) from equation (13), and estimate the following forecast error regression:

$$\begin{aligned} FE_{t+1} = \pi_0^{FE} + \pi_1^{FE} EBSI_t + \phi_1^{FE} INCSNCE_t + \phi_2^{FE} INCPNSI_t + \phi_3^{FE} EXCSNCE_t \\ + \phi_4^{FE} EXCPNSI_t + \zeta_{t+1}^{FE} \end{aligned} \tag{27}$$

where FE_{t+1} is one year ahead forecast error measured as $FE_{t+1} = STR_{t+1} - ANF_{t+1}$. Each variable coefficient in the forecast error regression is equal to its coefficient in the earnings regression minus its coefficient in the analysts forecast regression. For example; $\phi_1^{FE} = \phi_1^{STR} - \phi_1^{ANF}$, therefore a significant coefficient on ϕ_1^{FE} implies that analysts attach a weight to shifted negative core earnings, which is significantly different from the actual persistence of shifted negative core earnings. The sign of ϕ_1^{FE} in this case determines whether analysts underreact/overreact to information in negative special items. Given that shifted negative core earnings, and all negative special items compositions, are negative data values; a positive (negative) coefficient in this case means that analysts underreact (overreact) in reflecting that firms with higher shifted negative core earnings in the current period have less favorable future earnings outcomes, then forecast errors will be more negative (positive) for these firms, resulting in a positive (negative) association between shifted negative core earnings and forecast errors. However, if analysts' forecast is efficient, we expect to find insignificant coefficients on all included and excluded compositions of negative special items. We estimate the regressions using OLS and report the results in Table 7. The regressions are estimated for negative special items firms. When we run the regressions for all special items firms and include also positive special items as an additional explanatory variable, our results on the negative special items compositions do not change. For sake of brevity, we report the results for regressions estimated for only negative special items firms in Table 7.

Table 7 Panel A reports descriptive statistics. It shows that analysts forecast errors are negative, consistent with the overall optimism bias documented in prior studies (Bradshaw et al. 2001, Chen 2010). Table 7 Panel B presents results of the actual earnings and analysts forecast earnings regressions in column (I) and column (ii), respectively. The actual persistence of earnings before special items is 0.677 in column (I) in comparison to the analysts' implied estimate of persistence of 0.595 in column (ii). With regard to negative special items, only included components are significant in columns (I) and (ii).The actual (analysts' implied) persistence of included negative core earnings is 0.829 (0.698). The difference between the actual or analysts' implied persistence of included shifted negative core earnings and the persistence of earnings before special items in its respective regression is statistically insignificant (untabulated result of 0.19 F-value , 0.661 P-value in the actual earnings regression; and 0.13 F-value, 0.716 P-value in the analyst forecast regression). Included purified negative special items have an actual persistence of 0.114 and an analysts' implied persistence of 0.097 in columns (I) and (ii), respectively. Excluded components of negative special items are statistically insignificant. The coefficient on excluded shifted negative core earnings is positive and insignificant (0.043, *t*-statistic = 0.47) in column (I) and turns out to be negative but also insignificant (−0.007, *t*-statistic = −0.08) in column (ii). Excluded purified negative special items have insignificant and negative coefficients in columns (I) and (ii).

Table 7 Panel C presents results of the analysts forecast error regression. Results reveal that the analysts' under-reaction to information in earnings before special items is statistically significant at the 1% level, leading to systematic forecast errors. This result is consistent with prior research (Ahmed et al. 2005). Interestingly, all coefficients on negative special items compositions are unrelated to forecast errors. The only exception is the marginal significance at the 10% level of the coefficient on excluded purified negative special items[64]. Overall, the results demonstrate that analysts fully incorporate information in negative special items consistent with each negative special items differential implication on future earnings.

[Insert Table 7 here]

5.4.2 Additional Tests

For robustness check, we replicate the forecast error regression using different specifications to investigate if our results hold under differing disclosure environments, information environments, and after controlling for firm characteristics that might be related to analysts' ability to assess the persistence of earnings components. With regard to change in disclosure requirements, Chen (2010) find a change in analysts' ability to understand the persistence of some earnings exclusions after the introduction of Regulation G by the SEC, which came into effect on March 2003. This regulation requires managers disclosing non-GAAP earnings to also present GAAP earnings, which might affect the practice of expense misclassification by management and/or the analysts' understanding of persistence of earnings components. In order to test if our results are different pre and post the SEC intervention, we partition our negative special items sample into two subsamples; Pre-Regulation G (from 1991-2002) and Post-regulation G (2003-2012), and run the forecast error regression for each period subsample.

Previous research finds evidence of analysts differing understanding of persistence of earnings, which is relative to the flow of information surrounding the firm (See Weber 2009, Lev and Nissim 2004, Ahmed et al. 2005 among others). Following Weber (2009), we use analysts

[64] Note that purified negative special items (that are negative data values) have an insignificant negative coefficient in the actual earnings regression that is slightly larger in absolute value to the insignificant and negative coefficient in the earnings forecast regression, and that this difference is only statistically significant at the 10% level in the forecast error regression, which clearly shows a very minor under-reaction. This significance vanishes after adding controls in the next table, Table 8.

following as a proxy for information environment, and partition the negative special items sample into two subsamples of firms on the basis of the number of analysts following the firm relative to the annual cross section median of all firms with non-zero analysts' followings.

As a last check, we also add four additional controls to the negative special items sample. We add accruals, ACC_t, because negative special items comprise large accruals. We control for growth using market to book ratio, MTB_t, because firms with higher growth opportunities relative to assets in place may be more difficult to assess (Ahmed et al. 2005). We also add the natural logarithm of analysts following, COV_t, and change in sales, $\Delta SALE_t$. We report the results of all additional tests in Table 8.

Table 8 results reveal that the partition of sample does not affect the inferences from the forecast error regression with regard to negative special items compositions and only show differences in analysts' ability to assess earnings before special items. For example, the Post Regulation G subsample shows a significant coefficient of 0.055 on earnings before special items in comparison to a significant coefficient of 0.080 in the Pre Regulation G subsample. Also, the association of earnings before special items and forecast errors is much attenuated for firms with enhanced information environment, that is π_1^{FE} is equal to 0.079 with *t*-statistic of 9.01 in the Low Following subsample and decreases to 0.014 with a *t*-statistic of 2.26 in the High Following subsample. All negative special items have insignificant coefficients across different subsamples consistent with analysts' ability to track down the compositions of negative special items.

We obtain similar inferences with the addition of control variables to the negative special items sample in the last column of Table 8. The coefficient on earnings before special items is still significant and does not appear to be highly affected. The control variables results are qualitatively consistent with prior research (Ahmed et al. 2005 and Chen 2010). Again, all coefficients of negative special items are still insignificant. Also, the coefficient on excluded purified negative special that is marginally significant in the full sample becomes insignificant in the subsamples regressions and the regression with additional controls.

In sum, these results demonstrate analysts forecast efficiency with respect to negative special items components but not earnings before special items. Any differences between the actual persistence of negative special items components and the weights attached by analysts to these components appear to be insignificant and do not contribute to any related analysts forecast errors. However, another interpretation of this result does exist. If analysts always adjust actual street earnings to be the same basis as their forecast prior to earnings announcement by excluding the same special items, the actual-analysts' implied persistence results could be a manifestation of an arbitrary match of actual earnings adjustment and forecast basis. Nevertheless, the overall evidence in the paper is highly consistent with analysts' expertise in treating negative special items by including a negative special items construct that have more persistent implications on future earnings and operating cash flows; and taking an inclusion/exclusion decision that appears to be guided by their awareness of the underlying compositions of negative special items.

[Insert Table 8 here]

6. Conclusion

Negative special items are conceptually associated with significant firm-specific conditions that have uncertain consequences. Additionally, there is evidence of strategic reporting of negative core earnings as negative special items. This poses an identification problem for analysts when adjusting street earnings in order to develop an earnings metric that reflects more persistent earnings components. Therefore, analysts' treatment of special items is idiosyncratic and deals with special items at the firm-level. Prior research documents that street earnings' inclusions are more persistent than their exclusions, but does not examine the rationale underlying the analysts' adjustment process of negative special items. In this study, we provide such evidence of the rationale of the inclusions/exclusions of negative special items in the light of the fundamental composition of negative special items.

We first decompose negative special items into two fundamental components that reflect the recognition of unusual events (measure of purified negative special items) and the misclassification of earnings (measure of shifted negative core earnings). Our decomposition passes validation tests. We show that the purified measure is less persistent and has high asymmetric timeliness, but the shifted measure is more persistent and less asymmetrically timelier. This is consistent with the purified measure capturing transience caused by conditional conservatism, and that the shifted measure is a misclassified item that is conceptually unrelated to negative special items. These components represent the fundamental structure of negative special items.

We then investigate the properties of negative special items that analysts include in and exclude from street earnings. We apply extended decompositions on negative special items that ultimately yield four components: included shifted, included purified, excluded shifted and excluded purified. We find that analysts process information in negative special items and adjust street earnings to reflect only the more dominant components of negative special items that have higher persistence, which is in line with the fundamental composition of negative special items. In addition, logistics regression results show that analysts are more likely to include the shifted negative core earnings component of special items, and are aware of the motivations and conditions associated with the firm's negative special items recognition. We also provide evidence that the analysts' implied persistence for the four components is consistent with their actual persistence, such that future analysts forecast errors are not predictable by these components. This later result is robust to different disclosure environments and information environments, and also holds after controlling for factors associated with lower analysts' ability to assess earnings persistence.

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APPENDIX

Variable Definitions

Variable	Description	Measurement
NSI_t	Negative core earnings (level)	= [cost of goods sold (#41) + selling, general and administrative expenses (#189)] / sale (#12). If the values are missing, negative core earnings are calculated as the difference between sale (#12) and operating income before depreciation (#13), and divided by sale (#13).
ΔNCE_t	Negative core earnings (change)	$= NCE_t - NCE_{t-1}$
ATO_t	Assets turnover ratio	= [sale (#12) / average net operating assets]. Net operating assets = operating assets − operating liabilities = [total assets (#6) − cash (#1) and short term investments (#32)] − [total assets (#6) − total debt (#9 + #34) − book value of common (#60) and preferred equity (#130) − Minority Interest (# 38)]. Average NOA is required to be positive.
ΔATO_t	Change in asset turnover ratio	$= ATO_t - ATO_{t-1}$
ACC_t	Operating accruals	= [earnings before extraordinary items and discontinued operations (#123) − cash from operations (#308− #124)] / sale (#12)
$\Delta SALE_t$	Percentage change in sales	= [sale at year (t) – sale at year ($t-1$)] / sale at year (t)
$NEG\Delta SALE_t$	Negative percentage change in sales	$= \Delta SALE_t$ when $\Delta SALE_t < 0$, and zero otherwise.
BV_t	Ending book value	= common equity (#60) / sale (#12).
E_t	Earnings	Measured as; earnings = earnings before extraordinary items and discontinued operations (#123) / sale (#12), or abnormal earnings = [earnings before extraordinary items and discontinued operations (#123) / sale (#12)] – an implied cost of capital of 0.12 × book value at year ($t-1$).
CE_t	Core earnings	= operating income before depreciation (#13)= [sales − cost of goods sold− selling, general and administrative expenses (#13)] / sale (#12)
NSI_t	Negative special items	= [special items (#17) / sale (#12)] when special items are negative, and 0 otherwise.
PSI_t	Positive special items	= [special items (#17) / sale (#12)] when special items are positive, and 0 otherwise.

OTE_t	Earnings other than core earnings and negative special items	$= \left(E_t - CE_t - NSI_t\right)$ / sale (#12)
$SNCE_t$	Shifted negative core earnings	Measured using the classification decomposition approach described in text.
$PNSI_t$	Purified negative special items	$= NSI_t - SNCE_t$
AR_t	Abnormal returns	Measured as; size adjusted returns = The difference between the buy-hold returns and the buy-hold returns on the CRSP equally weighted market index over the same period. Returns measurement commences in April and ends in March next fiscal year. Delisting returns are used when available, and we substitute zeros for missing monthly returns following Campbell et al. (2010).
D_t	Negative abnormal return indicator variable	$D = 1$ when abnormal return is negative, and 0 otherwise.
$INCNSI_t$	Negative special items included in street earnings	$= NSI_t$ when street earnings = GAAP earnings, and zero otherwise. GAAP earnings are measured as the applicable basic or diluted earnings per share (#58 or #57), that is matched to IBES reported actual earnings per share.
$EXCNSI_t$	Negative special items excluded from street earnings	$= NSI_t$ when street earnings > GAAP earnings, and zero otherwise.
$INCSNCE_t$	Shifted negative core earnings included in street earrings	$= SNCE_t$ when $INCNSI_t \neq 0$, and zero otherwise
$INCPNSI_t$	Purified negative special items included in street earnings	$= PNSI_t$ when $INCNSI_t \neq 0$, and zero otherwise
$EXCSNCE_t$	Shifted negative core earnings excluded from street earrings	$= SNCE_t$ when $EXCNSI_t \neq 0$, and zero otherwise
$EXCPNSI_t$	Purified negative special items excluded from street earnings	$= PNSI_t$ when $EXCNSI_t \neq 0$, and zero otherwise
$ICONTAM_t$	Negative special items contaminated by shifted negative core earnings and included in street earnings	$= NSI_t$ when $INCNSI_t \neq 0$ and $SNCI_t \neq 0$, and zero otherwise

$ICLEAN_t$	Negative special items that are free of shifting and included in street earnings	$= NSI_t$ when $INCNSI_t \neq 0$ and $SNCI_t = 0$, and zero otherwise
$ECONTAM_t$	Negative special items contaminated by shifted negative core earnings and excluded from street earnings	$= NSI_t$ when $EXCNSI_t \neq 0$ and $SNCI_t \neq 0$, and zero otherwise
$ECLEAN_t$	Negative special items that are free of shifting and excluded from street earnings	$= NSI_t$ when $EXCNSI_t \neq 0$ and $SNCI_t = 0$, and zero otherwise
OCF_t	Operating cash flows	Measured as cash flow from operating activities (#308) and divided by sale (#13).
$EBSI_t$	Earnings before special items	Measured as earnings before special items per share (#233), and divided by assets per share
$INCLUSION_t$	Negative special items inclusion indicator	Coded as one when $INCNSI_t \neq 0$, and zero when $EXCNSI_t \neq 0$
$SHIFTED_t$	Shifted negative core earnings indicator	Coded as one when $SNCE_t \neq 0$, and zero otherwise.
$PURIFIED_t$	Purified negative special items indicator	Coded as one when $PNSI_t \neq 0$, and zero otherwise.
$SMOOTH_t$	Smoothing measure	Measured as volatility of operating cash flow (#308) divided by volatility of earnings after special items and before extraordinary items (#123). Volatility of operating cash flows and earnings are measured as the standard deviation over the same five rolling five-year time windows. We require at least three non-missing observations.
COV_t	Analysts coverage	Measured as the natural logarithm of the number of analysts following the firm.
FRE_t	Frequency of negative special items reporting indicator	Coded as one if the firm reported non-zero negative special items over the past two years, and zero otherwise.
HIS_t	History of negative special items treatment indicator	Coded as one if the analysts included negative special items in street earnings over the past two years, and zero otherwise.

BTM_t	Book to market ratio	Measured as total common equity (#60) divided by market value (#25×stock price from CRSP).
MER_t	Significant merger and acquisitions indicator	Coded as one if annual acquisitions (#129) are greater than 20% of lagged total assets (#6) , and zero otherwise.
ROA_t	Return on assets	Measured as earnings after special items and before extraordinary items (#123) divided by lagged total assets.
MAG_t	Negative special items magnitude indicator	Coded as one if negative special items are higher than the annual cross section mean of non-zero negative special items, and zero otherwise.
STR_t	Street earnings	Measured as IBES reported actual earnings per share from IBES unadjusted detail actual file, and divided by assets per share.
ANF_t	Most recent forecast of earnings per share	Measured as IBES median consensus forecast of earnings per share from the IBES unadjusted summary file, and divided by assets per share.
FE_t	Forecast error	$= STR_t - ANF_t$

Tables

Table 1

Negative Core Earnings Models Fit Statistics

Panel A: Negative Core Earnings Level

$$NCE_t = \eta_0 + \eta_1 NCE_{t-1} + \eta_2 ATO_t + \eta_3 ACC_{t-1} + \eta_4 ACC_t + \eta_5 \Delta SALE_t + \eta_6 NEG\Delta SALE_t + \xi_t$$

Variables	Predicted sign	Mean coefficients (OLS)	Median coefficients (Quintile Regression)
Intercept		0.180***	0.085***
		(33.72)	(19.95)
NCE_{t-1}	+	0.795***	0.906***
		(118.96)	(190.91)
ATO_t	+	0.002***	0.001***
		(5.82)	(9.51)
ACC_{t-1}	+	0.208***	0.150***
		(22.04)	(29.23)
ACC_t	−	−0.292***	−0.112***
		(−25.68)	(−23.35)
$\Delta SALE_t$	−	−0.211***	−0.072***
		(−25.86)	(−25.35)
$NEG\Delta SALE_t$	−	−0.070***	−0.096***
		(−5.25)	(−12.73)
Adj.R^2		76%	73%

Panel B: Negative Core Earnings change

$$\Delta NCE_t = \theta_0 + \theta_1 NCE_{t-1} + \theta_2 \Delta NCE_{t-1} + \theta_3 \Delta ATO_t + \theta_4 ACC_{t-1} + \theta_5 ACC_t + \theta_6 \Delta SALE_t + \theta_7 NEG\Delta SALE_t + \varepsilon_t$$

Variables	Predicted sign	Mean coefficients (OLS)	Median coefficients (Quintile Regression)
Intercept		0.136***	0.118***
		(29.06)	(28.83)
NCE_{t-1}	−	−0.144***	−0.127***
		(−25.61)	(−28.70)
ΔNCE_{t-1}	−	−0.025***	−0.013**
		(−2.84)	(−2.17)
ΔATO_t	−	−0.006***	−0.002***
		(−10.62)	(−9.74)
ACC_{t-1}	+	0.170***	0.176***
		(23.41)	(37.32)
ACC_t	−	−0.221***	−0.105***
		(−28.85)	(−27.11)
$\Delta SALE_t$	−	−0.229***	−0.083***
		(−29.98)	(−26.79)
$NEG\Delta SALE_t$	−	−0.0131	−0.096***
		(−1.21)	(−13.61)
Adj.R^2		35%	31%

The sample consists of 72,447 firm-year observations on the Compustat-CRSP intersection from 1989 to 2012. t-statistics are clustered by firm and shown in parentheses.*,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively. All variables are defined in the appendix. NCE_t (Negative core earnings) is a positive data item. In Panel A, using a censored regression (Tobit model) yields similar coefficients to the OLS regression.

Table 2

Regressions of Unexpected Negative Core Earnings on Negative Special Items

Panel A: Regression of Current Unexpected Negative Core Earnings Levels on Negative Special Items

$$UNCE_t = \phi_0 + \phi_1 NSI_t + \zeta_t$$

Variables	Predicted sign	Dependent variable = $UNCE_t$ OLS Coefficients The full sample	Negative special Items subsample
Intercept		0.001 (0.98)	−0.001 (−0.50)
NSI_t	−	−0.042*** (−2.74)	−0.038** (−2.19)
Adj.R^2		0.03%	0.08%
Sample size		67,859	27,174

Panel B: Regression of Next Year Unexpected Negative Core Earnings Changes on Negative Special Items

$$U\Delta NCE_{t+1} = \varphi_0 + \varphi_1 NSI_t + \upsilon_{t+1}$$

Variables	Predicted sign	Dependent variable = $U\Delta NCE_{t+1}$ OLS Coefficients The full sample	Negative special Items subsample	Imposing a non-zero restriction on next year negative special items
Intercept		−0.002*** (−2.63)	-0.00937*** (-3.53)	-0.002 (-1.39)
NSI_t	+	0.034*** (2.64)	0.0549*** (3.33)	0.012 (0.65)
NSI_{t+1}				−0.036** (−2.00)
Adj.R^2		0.02%	0.06%	0.15%
Sample size		56,328	21,514	22,765

Standard errors are clustered by firm and year.*,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively. All variables are defined in the appendix. NSI_t are measured in absolute terms.

Table 3

Validation of the Decomposition Approach and Forecasting Future Earnings

$$E_{t+1} = \omega_0 + \omega_1 CE_t + \lambda_0 NSI_t + \omega_3 OTE_t + \omega_4 BV_t + \vartheta.IY + \zeta_{t+1}$$

$$E_{t+1} = \omega_0 + \omega_1 CE_t + \lambda_1 SNCE_t + \lambda_2 PNSI_t + \omega_3 OTE_t + \omega_4 BV_t + \vartheta.IY + \zeta_{t+1}$$

Panel A: Descriptive Statistics for Main Continuous Variables in the Full Compustat-CRSP Sample

	Full Compustat-CRSP sample				**Non-zero special items components**			
			Percentile				**Percentile**	
Variables	**Mean**	**SD**	**(5)**	**(95)**	**Mean**	**SD**	**(5)**	**(95)**
TSI_t	−0.026	0.102	−0.158	0.014	−0.050	0.136	−0.312	0.041
NSI_t	−0.030	0.099	−0.158	0	−0.075	0.145	−0.408	−0.001
$SNCE_t$	−0.003	0.012	−0.016	0	−0.013	0.021	−0.077	−0.000
$PNSI_t$	−0.027	0.093	−0.142	0	−0.070	0.138	−0.385	−0.001
PSI_t	0.004	0.019	0	0.014	0.030	0.045	0.001	0.151
CE_t	0.070	0.383	−0.419	0.468				
OTE_t	−0.107	0.143	−0.388	0.017				
BV_t	0.842	1.148	0.049	2.634				

Panel B: Regression of Next Year Earnings on Negative Special Items and its Compositions

Var.	Dependent earnings variable = One year ahead earnings			
Intercept	−0.119*** (−52.37)	−0.0266 (−1.03)	−0.119*** (−52.38)	−0.0248 (−0.96)
CE_t	0.841*** (69.12)	0.839*** (65.35)	0.841*** (69.13)	0.839*** (65.38)
NSI_t	0.502*** (13.89)	0.282*** (7.97)		
$SNCE_t$			0.835*** (3.01)	0.671** (2.52)
$PNSI_t$			0.477*** (10.83)	0.252*** (5.84)
OTE_t		0.662*** (25.16)		0.663*** (25.18)
BV_t		−0.055*** (−16.15)		−0.055*** (−16.18)
IY	No	Yes	No	Yes
Wald Test				
$\omega_1 = \lambda_0$	F=70.05 [P=0.00]	F=188.64 [P=0.00]		
$\omega_1 = \lambda_1$			F=0.00 [P=0.981]	F=0.40 [P=0.529]
$\omega_1 = \lambda_2$			F=57.88 [P=0.00]	F=152.38 [P=0.00]
Adj.R^2	48%	55%	48%	55%

Panel C: Regression of Next Year Abnormal Earnings on Negative Special Items and its Compositions

Var.	Dependent earnings variable = One year ahead abnormal earnings			
Intercept	−0.216*** (−96.08)	−0.040* (−1.68)	−0.216*** (−96.21)	−0.038 (−1.60)
CE_t	0.878*** (77.47)	0.783*** (69.34)	0.879*** (77.43)	0.783*** (69.35)
NSI_t	0.595*** (16.75)	0.264*** (8.30)		
$SNCE_t$			1.011*** (3.63)	0.686*** (2.82)
$PNSI_t$			0.564*** (13.21)	0.232*** (6.06)
OTE_t		0.612*** (25.86)		0.613*** (25.88)
BV_t		−0.164*** (−55.26)		−0.164*** (−55.29)
IY	No	Yes	No	Yes
Wald Test				
$\omega_1 = \lambda_0$	F=50.17 [P=0.00]	F=205.29 [P=0.00]		
$\omega_1 = \lambda_1$			F=0.23 [P=0.635]	F=0.16 [P=0.690]
$\omega_1 = \lambda_2$			F=45.32 [P=0.00]	F=171.47 [P=0.00]
Adj.R^2	46%	56%	46%	56%

The table provides results of pooled OLS regressions of two measures of future earnings on negative special items compositions. The sample includes 56,328 observations in the Compustat-CRSP sample from 1989 to 2012. Standard errors are robust standard error.*,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively. IY is a set of dummy variables that represent the industry association, based on two digit SIC code, and the year. Negative special items and their components are negative data values. All variables are defined in the appendix.

Table 4

Validation of the Decomposition Approach and Asymmetric Timeliness of Special Items

$$SPECIAL_t = \beta_0 + \beta_1 D_t + \beta_2 AR_t + \beta_3 AR_t * D_t + \varepsilon_t$$

Panel A: Asymmetric Timelines of Total Special Items, Positive Special Items and Negative Special Items

Variables	Coefficients	Dependent $SPECIAL_t$ component		
		TSI_t	PSI_t	NSI_t
Intercept	β_0	−0.028***	0.007***	−0.035***
		(−27.27)	(26.57)	(−35.79)
D_t	β_1	0.010***	−0.000	0.011***
		(5.68)	(−0.99)	(6.13)
AR_t	β_2	−0.003***	0.001***	−0.004***
		(−2.75)	(3.63)	(−3.88)
$AR_t * D_t$	β_3	0.120***	−0.001	0.122***
		(27.59)	(-1.63)	(28.64)
Adj.R^2		5%	0.1%	5%

Panel B: Asymmetric Timelines of Negative Special Items Compositions

Variables	Coefficients	Dependent $SPECIAL_t$ component	
		$PNSI_t$	$SNCE_t$
Intercept	β_0	−0.042***	−0.005***
		(−34.01)	(−30.74)
D_t	β_1	0.010***	0.001***
		(4.79)	(2.96)
AR_t	β_2	−0.005***	−0.001***
		(−3.73)	(−3.89)
$AR_t * D_t$	β_3	0.127***	0.009***
		(26.54)	(15.73)
Adj.R^2		5.7%	1.7%

The table provides results of pooled OLS regressions of different components of special items on measures of abnormal returns that proxy for good and bad news. In Panel A: the sample includes 35,585 observations for non-zero special items firms in the Compustat-CRSP sample. In Panel B: the sample includes 27,174 observations for non-zero negative special items firms in the Compustat-CRSP sample. Standard errors are robust standard error.*,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively. All variables are defined in the appendix.

Table 5

Future Cash Implications of Extended Decompositions of Negative Special Items

$$OCF_{t+1} = \gamma_0 + \gamma_1 EBSI_t + \rho SPECIAL_t + \varepsilon_{t+1}$$

Panel A: Descriptive Statistics for Main Continuous Variables in the Compustat-CRSP-IBES Sample

	Compustat-CRSP-IBES sample for non-zero negative special items				Non-zero special items components			
			Percentile				Percentile	
Variables	Mean	SD	(5)	(95)	Mean	SD	(5)	(95)
$INCNSI_t$	−0.006	0.044	−0.014	0	−0.046	0.114	−0.233	−0.000
$EXCNSI_t$	−0.060	0.133	−0.323	0	−0.081	0.149	−0.429	−0.001
$INCSNCE_t$	−0.001	0.005	−0.001	0	−0.008	0.017	−0.046	−0.000
$INCPNSI_t$	−0.005	0.041	−0.011	0	−0.043	0.109	−0.223	−0.000
$EXCSNCE_t$	−0.007	0.015	−0.034	0	−0.013	0.021	−0.076	−0.000
$EXCPNSI_t$	−0.054	0.126	−0.298	0	−0.075	0.143	−0.406	−0.001
$ICONTAM_t$	−0.004	0.037	−0.005	0	−0.052	0.126	−0.270	−0.000
$ICLEAN_t$	−0.002	0.024	−0.001	0	−0.037	0.096	−0.181	−0.000
$ECONTAM_t$	−0.039	0.114	−0.219	0	−0.090	0.160	−0.524	−0.002
$ECLEAN_t$	−0.021	0.079	−0.103	0	−0.068	0.132	−0.323	−0.001
OCF_t	0.053	0.131	−0.192	0.218				
$EBSI_t$	−0.012	0.164	−0.344	0.143				

Panel B: CLASSIFICATION DECOMPOSITION (CLDE) level

The sample	Variables					Adj.R^2
	Intercept	$EBSI_t$	$SNCI_t$	$PNSI_t$	PSI_t	
(A)	0.065***	0.538***	0.151**	0.017	−0.256***	38.2%
	(72.23)	(47.29)	(2.13)	(1.38)	(−6.16)	
(B)	0.065***	0.524***	0.148**	0.023*		38.3%
	(64.94)	(42.70)	(2.09)	(1.87)		

Panel C: ANALYSTS DECOMPOSITION (ANDE) level

The sample	Variables					Adj.R^2
	Intercept	$EBSI_t$	$INCNSI_t$	$EXCNSI_t$	PSI_t	
(A)	0.064***	0.539***	0.132***	0.011	−0.250***	38.2%
	(72.13)	(47.51)	(4.09)	(1.00)	(−6.00)	
(B)	0.064***	0.526***	0.138***	0.016		38.3%
	(64.84)	(42.92)	(4.26)	(1.45)		

Panel D: ANALYSTS-CLASSIFICATION DECOMPOSITION (ANCLDE) level

The sample	Variables							Adj.R^2
	Intercept	$EBSI_t$	$INCSNCE_t$	$INCPNSI_t$	$EXCSNCE_t$	$EXCPNSI_t$	PSI_t	
(A)	0.064***	0.539***	0.630**	0.0943**	0.103	0.004	−0.252***	38.3%
	(72.45)	(47.54)	(2.22)	(2.31)	(1.36)	(0.33)	(−6.05)	
(B)	0.064***	0.526***	0.637**	0.100**	0.098	0.0102		38.4%
	(65.17)	(42.95)	(2.24)	(2.46)	(1.30)	(0.78)		

Panel E: ANALYSTS-CLASSIFICATION SORTING (ANCLSO) level

The sample	Variables							Adj.R^2
	Intercept	$EBSI_t$	$ICONTAM_t$	$ICLEAN_t$	$ECONTAM_t$	$ECLEAN_t$	PSI_t	
(A)		0.539***	0.155***	0.081	0.019	−0.009	−0.249***	38.2%
		(47.57)	(4.28)	(1.28)	(1.54)	(−0.50)	(−5.98)	
(B)		0.526***	0.161***	0.087	0.024*	−0.004		38.4%
		(42.99)	(4.41)	(1.38)	(1.92)	(−0.23)		

The table provides results of pooled OLS of future operating cash flows on different measures of earnings. Each panel provides results corresponding to different decompositions of negative special items. Decompositions levels are defined in text and in Figure 2. Sample (A) includes 20,149 observations for non-zero special items firms in the Compustat-CRSP-IBES sample. Sample (B) includes 15,654 observations for non-zero negative special items firms in the Compustat-CRSP-IBES sample. Standard errors are robust standard error.*,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Negative special items and their components are negative data values and positive special items are positive data values. All variables are defined in the appendix.

Table 6

Analysts' Negative Special Items Inclusion Decision

$$INCLUSION_t = \kappa_0 + \kappa_1 SHIFTED_t + \kappa_2 PURIFIED_t + \kappa_3 SMOOTH_t + \kappa_4 COV_t + \kappa_5 FRE_t + \kappa_6 HIS_t + \kappa_7 BTM_{t-1} + \kappa_8 MER_t + \kappa_9 ROA_{t-1} + \kappa_{10} MAG_t + \xi_t$$

Panel A: Descriptive Statistics for the Main Continuous Variables

Compustat-CRSP-IBES sample for non-zero negative special items

			Percentile	
Variables	**Mean**	**SD**	**(5)**	**(95)**
$SMOOTH_t$	1.520	1.741	0.187	4.492
COV_t	1.445	1.003	0	2.100
BTM_t	0.643	0.596	0.053	1.767
ROA_t	−0.017	0.156	−0.354	0.166

Panel B: Logistic Regression and Ordinary Least Square Coefficients Results for Dichotomous Analysts' Negative Special Items Inclusion Decision

Variables	Coefficients	Predicted sign	LOGIT		OLS-LPM
			Coefficient (*z*-Statistic)	**MEM**	**Coefficient (*t*-Statistic)**
Intercept	κ_0	−	−0.926*** (−5.22)		0.259*** (10.09)
$SHIFTED_t$	κ_1	+	0.125** (2.31)	0.015	0.015** (2.34)
$PURIFIED_t$	κ_2	−	−0.093 (−0.58)	−0.012	−0.015 (−0.64)
$SMOOTH_t$	κ_3	+	0.041*** (2.88)	0.004	0.006*** (2.61)
COV_t	κ_4	−	−0.254*** (−8.81)	−0.030	−0.032*** (−8.75)
FRE_t	κ_5	?	−0.405*** (−6.84)	−0.049	−0.046*** (−7.00)
HIS_t	κ_6	?	1.802*** (10.02)	0.216	0.311*** (7.66)
BTM_{t-1}	κ_7	−	−0.148*** (−2.68)	−0.018	−0.019*** (−2.69)
MER_t	κ_8	−	−0.299*** (−5.42)	−0.036	−0.036*** (−5.44)
ROA_{t-1}	κ_9	−	−0.705*** (−3.46)	−0.084	−0.086*** (−3.25)
MAG_t	κ_{10}	−	−0.790*** (−10.45)	−0.095	−0.084*** (−11.90)
Adj.R^2			4%		3%
Sample size			11,964		11,964

The table provides results of logistic and linear probability models of the determinants of the analysts' decision of negative special items inclusion. The sample is comprised of non-zero negative special items firms in the Compustat-CRSP-IBES sample MEM is the marginal effect at means. z-statistic and t-statistic are calculated using robust standard errors. All variables are defined in the appendix. *,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 7

Actual Earnings Process, Analysts Expectation and Negative Special Items Compositions Predictability of Forecast Errors

$$STR_{t+1} = \pi_0^{STR} + \pi_1^{STR} EBSI_t + \phi_1^{STR} INCSNCE_t + \phi_2^{STR} INCPNSI_t + \phi_3^{STR} EXCSNCE_t + \phi_4^{STR} EXCPNSI_t + \zeta_{t+1}^{STR}$$
$$ANF_{t+1} = \pi_0^{ANF} + \pi_1^{ANF} EBSI_t + \phi_1^{ANF} INCSNCE_t + \phi_2^{ANF} INCPNSI_t + \phi_3^{ANF} EXCSNCE_t + \phi_4^{ANF} EXCPNSI_t + \zeta_{t+1}^{ANF}$$

Panel A: Descriptive Statistics for the Main Continuous Variables

Compustat-CRSP-IBES sample for non-zero negative special items

			Percentile	
Variables	**Mean**	**SD**	**(5)**	**(95)**
STR_t	−0.004	0.156	−0.312	0.142
ANF_t	0.009	0.134	−0.250	0.145
FE_t	−0.012	0.052	−0.090	0.017

Panel B: Actual Earnings and Analysts Forecast Earnings Regressions

Var.	**Dependent earnings variable**			
	Column (I)		**Column (ii)**	
	Coeff.	**Future actual earnings**	**Coeff.**	**Future analysts forecast earnings**
Intercept	π_0^{STR}	0.036*** (3.90)	π_0^{ANF}	0.039*** (4.91)
$EBSI_t$	π_1^{STR}	0.677*** (43.80)	π_1^{ANF}	0.595*** (44.88)
$INCSNCE_t$	ϕ_1^{STR}	0.829** (2.40)	ϕ_1^{ANF}	0.698** (2.48)
$INCPNSI_t$	ϕ_2^{STR}	0.114** (2.34)	ϕ_2^{ANF}	0.097** (2.44)
$EXCSNCE_t$	ϕ_3^{STR}	0.043 (0.47)	ϕ_3^{ANF}	−0.007 (−0.08)
$EXCPNSI_t$	ϕ_4^{STR}	−0.023 (−1.32)	ϕ_4^{ANF}	−0.010 (−0.70)
Adj.R^2		48%		50%
Sample size		15,427		15,652

Panel C: Forecast Error Regression

$$FE_{t+1} = \pi_0^{FE} + \pi_1^{FE} EBSI_t + \phi_1^{FE} INCSNCE_t + \phi_2^{FE} INCPNSI_t + \phi_3^{FE} EXCSNCE_t + \phi_4^{FE} EXCPNSI_t + \zeta_{t+1}^{FE}$$

	Dependent earnings variable: Future forecast error							
Var.	Intercept	$EBSI_t$	$INCSNCE_t$	$INCPNSI_t$	$EXCSNCE_t$	$EXCPNSI_t$	Adj.R^2	Sample size
Coeff.	π_0^{FE}	π_1^{FE}	ϕ_1^{FE}	ϕ_2^{FE}	ϕ_3^{FE}	ϕ_4^{FE}		
	−0.009**	0.069***	0.0156	0.007	0.013	−0.012*	7%	15,427
	(−1.98)	(10.91)	(0.11)	(0.29)	(0.38)	(−1.90)		

The table provides OLS results of regressing future actual earnings, future forecast earnings, and future forecast error on earnings components. The sample is comprised of non-zero negative special items firms in the Compustat-CRSP-IBES sample. We include industry and year fixed effects in all regressions. All variables are defined in the appendix. *,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 8

Additional Tests on the Association of Negative Special Items Compositions with Analysts Forecast Errors

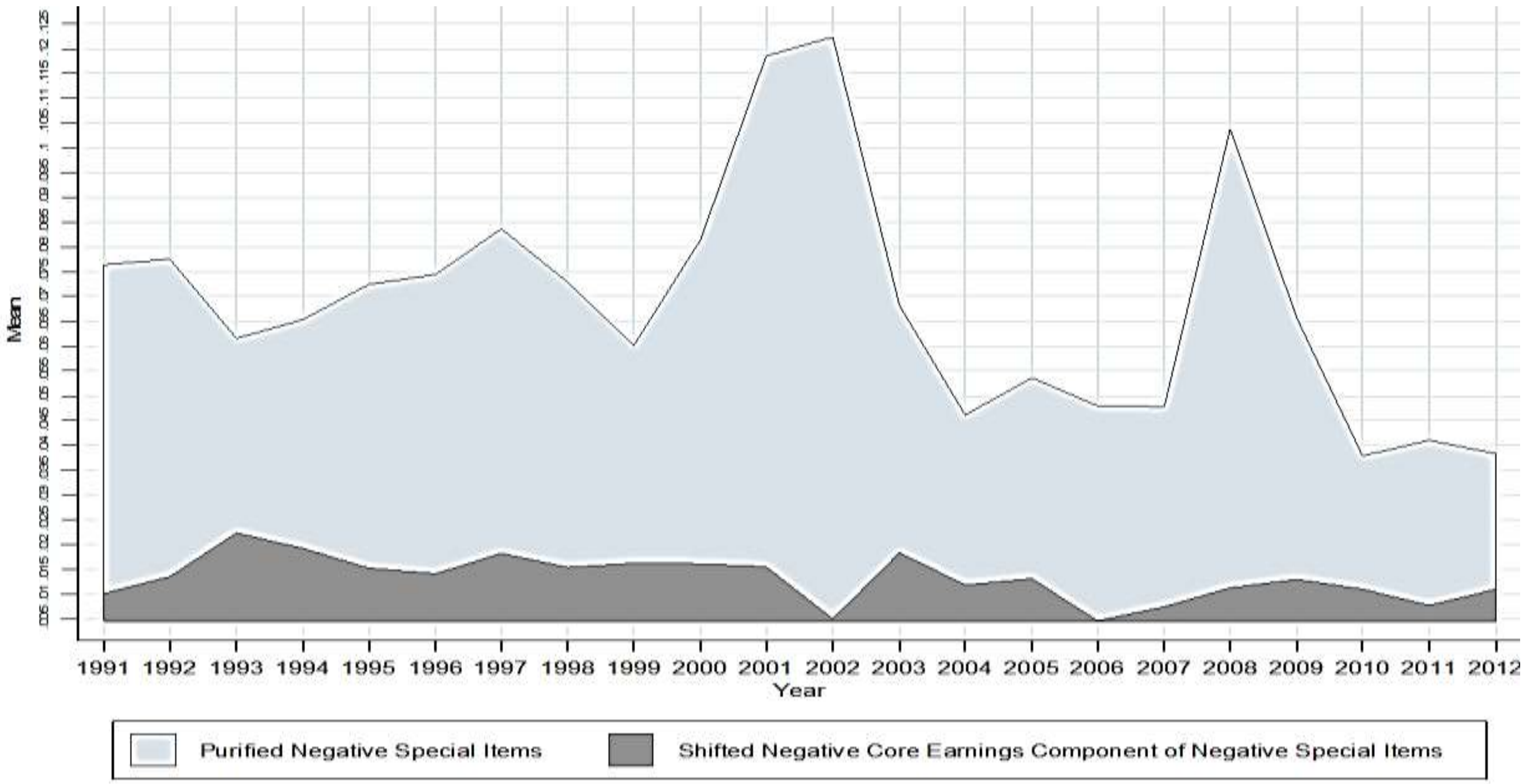
Variables	Coeff.	Firms' Disclosure environment		Firms' Information environment		Additional Controls
		Pre Regulation G	Post Regulation G	Low Following	High Following	
Intercept	π_0^{FE}	−0.003 (−0.62)	−0.002 (−0.71)	−0.016* (−1.96)	−0.004 (−1.04)	−0.019*** (−4.30)
$EBSI_t$	π_1^{FE}	0.080*** (8.67)	0.055*** (6.67)	0.079*** (9.01)	0.014** (2.26)	0.061*** (9.02)
$INCSNCE_t$	ϕ_1^{FE}	−0.098 (−0.46)	0.073 (0.41)	0.019 (0.11)	−0.078 (−0.42)	−0.006 (−0.04)
$INCPNSI_t$	ϕ_2^{FE}	−0.034 (−0.76)	0.020 (0.80)	−0.016 (−0.70)	0.057 (1.36)	0.012 (0.53)
$EXCSNCE_t$	ϕ_3^{FE}	0.004 (0.08)	0.039 (0.84)	0.009 (0.14)	0.017 (0.64)	0.014 (0.40)
$EXCPNSI_t$	ϕ_4^{FE}	−0.014 (−1.55)	−0.013 (−1.53)	−0.006 (−0.61)	−0.003 (−0.72)	0.001 (0.16)
ACC_t	ρ_1^{FE}					−0.007** (−2.31)
MTB_t	ρ_2^{FE}					−0.000 (−0.96)
COV_t	ρ_3^{FE}					0.006*** (13.54)
$\Delta SALE_t$	ρ_4^{FE}					0.005** (2.37)
Adj.R^2		7%	6%	8%	3%	8%
Sample size		6,767	8,660	7,121	8,306	15,396

The table provides OLS results of regressing future forecast error on earnings components using reduced sub-samples and additional controls. We use reduced samples of non-zero negative special items firms in the Compustat-CRSP-IBES sample. We include industry and year fixed effects in all regressions. Pre Regulation G corresponds to sample firms between 1991-2002; and Post-Regulation G corresponds to sample firms between 2003-2012. Low Following (High Following) subsamples are based on the number of analysts following the firm in non-zero followings that is lower than (higher than) annual cross section median of analysts following. All variables are defined in the appendix. *,**,*** denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Figures

Figure 1

Negative Special Items Decomposition Using an Expense-Expense Approach



The figure shows the means of non-zero values of components of negative special items over years. The decomposition of negative special items is based on 917 industry-year regressions of unexpected negative core earnings on negative special items. Negative coefficients between zero and negative one, which are consistent with classification shifting, are multiplied by actual negative special items of firms in the industry-year group to measure shifted negative core earnings at the firm level. Purified negative special items are the difference between actual negative special items and shifted negative core earnings. Imposing a non-zero negative special items restriction on the industry-year groups yields an overall similar picture of decomposed negative special items.

Figure 2

Earnings Components Used in the Analysis

	EBEIDO					
	EBSI	*NSI*				*PSI*
CLDE	*EBSI*	*SNCE*		*PNSI*		*PSI*
ANDE	*EBSI*	*INCNSI*		*EXCNSI*		*PSI*
ANCLDE	*EBSI*	*INCSNCE*	*INCPNSI*	*EXCSNCE*	*EXCPNSI*	*PSI*
ANCLSO	*EBSI*	*ICONTAM*	*ICLEAN*	*ECONTAM*	*ECLEAN*	*PSI*

Negative Special Items Firms only

All Special Items Firms

This figure presents a description of the earnings components used in the analysis in relation to the level of decomposition of negative special items. All earnings components in any level sum to *EBEIDO*, which is earnings before extraordinary items and discontinued operations. *EBEIDO* is divided into earnings before special items, *EBSI*, negative special items, *NSI*, and positive special items, *PSI*. Subsequent decomposition levels are decompositions of negative special items as explained in text. CLDE is the CLASSIFICATION DECOMPOSITION level of negative special items into shifted negative core earnings, *SNCE*, and purified negative special items, *PNSI* components. ANDE is the ANALYSTS DECOMPOSITION of negative special items into negative special items included in street earnings, *INCNSI*, and negative special items excluded from street earnings, *EXCNSI*. ANCLDE is the ANALYSTS-CLASSIFICATION decomposition into shifted negative core earnings included in street earnings, *INCSNCE*, purified negative special items included in street earnings, *INCPNSI*, shifted negative core earnings excluded from street earnings, *EXCSNCE*, purified negative special items excluded from street earnings, *EXCPNSI*.ANCLSO is ANALYSTS-CLASSIFICATION SORTING that categorizes negative special items into negative special items contaminated by shifted negative core earnings and included in street earnings, *ICONTAM*, negative special items that are totally free of shifting and included in street earnings, *ICLEAN*, negative special items contaminated by shifted negative core earnings and excluded from street earnings, *ECONTAM*, and negative special items that are totally free of shifting and excluded from street earnings, *ECLEAN*. Detailed definitions and measurement of variables are provided in the appendix.

Chapter 6: Conclusion

The inherent uncertainty associated with negative special items recognition and the suspects for strategic reporting make special items being viewed by investors and analysts as a "black box". While negative special items conceptually represent unusual or infrequent items that are not persistent, misclassifying some core operating expenses as negative special items "injects" a core element in this theoretically transitory earnings component. Research documents a substantial increase in the magnitude and frequency of negative special items that might make special items "no-special" anymore. This thesis extends this line of research, analytically and empirically, by showing different properties of special items that are based on the composition of special items and the motives and circumstances behind special items reporting.

In Chapter three, we develop an analytical framework that links the evolution of a set of accounting variables, including shifted core earnings and purified transitory earnings, to their weights in equity valuation models. Using special items as an objective measure of a transitory line item contaminated with core earnings, we construct an innovative measure of shifted negative core earnings at the firm-year-level. Building on our framework, we find empirically that reported special items have limited forecasting ability with respect to one year ahead abnormal earnings, however shifted negative core earnings forecast one year ahead abnormal earnings as if they are reported core earnings and purified special items evolve as a transitory component. We model an expected bad news impact of shifted negative core earnings on future profitability beyond their accounting informational role. Empirical results show that the theoretical bad news signal manifests in abnormal earnings forecast, but rather has a modest effect on the forecasting coefficient of shifted negative core earnings. With respect to valuation, we find that stock prices do not fully reflect the heterogeneity between the core and transitory components of special items, but rather overstate the entire amount of reported special items when classification shifting is suspected.

In Chapter four, we articulate a conceptual framework that associates negative special items reporting with the manager's motive to enhance reported earnings via earnings misclassification. This framework also links the market valuation of reported negative special items to the investors' perception of signals of misclassification. We then empirically investigate the manager's incentive, and whether the manager's preferred classifications represent GAAP-violation or allowable-management discretion. In addition, we examine the stock price reaction to negative special items conditional on an informative misclassification signal and a reporting misclassification signal. We find that, large reported negative special items are prevalent when current expected core earnings fall below last year reported core earnings, and that the higher magnitude of negative special items in this case is associated with GAAP-violation rather than within-GAAP discretion. The results reveal that the ability of negative special items to forecast lower future earnings is mainly attributable to negative core earnings misclassification, such that only the misclassified core component of negative special items rather than real negative special items forecast future earnings for a horizon up to three years similar to reported core earnings in the income statement. We believe that this finding is important because it reconciles the standard financial analysis textbooks suggestions of the exclusion of special items when forecasting earnings with the research results of negative special items persistence. We argue that this exclusion is “less harmful”, if it is only applied on adjusted (real) special items that represent unusual economic events. Quantifying the core composition of negative special items makes this adjustment plausible. We also find that the market values negative special items in correspondence with a reporting signal of misclassification that proves to be noisy, because the change in the predictive ability of negative special items is inconsistent with the signal. Moreover, an identified informative signal of misclassification that is consistent with the change in the predictive ability of negative special items does not lead to a corresponding stock price reaction to negative special items.

In Chapter four, we examine the analysts’ treatment of negative special items in arriving at street earrings, and whether this treatment reflects analysts’ awareness of the circumstances and motivations associated with negative special items reporting by firms. We develop direct measures of the core and transitory components of negative special items, and validate the measures using a forecasting test and a conditional conservatism test. We apply extended decompositions on negative special items that reflect different components of negative special items included in and excluded from street earrings. We find that analysts have expertise in processing negative special items to determine their level of permanence and adjust street earnings accordingly. Analysts include in street earnings the components of negative special items that lead to predictably lower future operating cash flows. The results reveal that the analysts’ inclusion decision reflects analysts’ understanding of the conditions (e.g. repeated negative special items recognition, merger-related charges, and poor performance) and motivations (e.g. misclassification of expenses and smoothing of income) associated with negative special items reporting by firms. We also find that the analysts' adjustment of negative special items fully incorporates the implications of different components of special items for future earnings and does not lead to predictable analysts' forecast errors. Partitioning the sample to reflect different disclosure and information environments or using an augmented model that incorporates controls associated with lower analysts' forecast efficiency, do not change inferences.